SCHEDULE REARRANGEMENTS IN THE AUTONOMOUS VEHICLE ERA

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Schedule Rearrangements in the Autonomous Vehicle era :An Empirical Study

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ABSTRACT

Autonomous vehicles are expected to become an inevitable reality in the coming years, as their uncovered benefits are increasingly proven to be positive, such as increased safety and traffic efficiency. However, their impacts on travel choices have often been represented with an assumed reduction in the travel time penalty, which oversimplified AVs' subsequent effects activity-travel scheduling choices. As such, models and assessment methods do not accurately represent travel behavior implications of autonomous vehicles. Thus, using survey data, this thesis identifies possible rearrangements in activity-travel schedules, classifies the respondents into classes with similar profiles of expected rearrangements, and identifies further classification on the basis of socio-economic, personal, and travel characteristics. The survey to be used is one in which respondents were asked to report a full, regular working day activity schedule using their currently preferred mode of transport, then report the schedule as they expect it to be if they could use an autonomous vehicle. The initial exploration of the data identified the occurrence of activities on-board (work, spare-time, meals, and getting ready), changes to the duration of activities outside travel, as well as travel (delay of work-bound trips, and advancement of home-bond trips). Next, we used latent class models to cluster the responses with respect to on-board activity duration changes, stationary activity duration changes, and travel departure time changes. The clustering uncovered types of classes: *no change, single activity on-board (work and spare-time), multiple activities on-board*. Interactions between stationary and on-board activities were identified, with some direct activity transfer to travel episode being common (with work, meals, and getting ready), while other activities were generally not transferred (spare-time). Finally,the addition of personal characteristics and demographics highlighted the limited influence of socio-economic factors, with the exception of education, on activity changes. In contrast, the most significant factors were mostly associated with work (daily time pressure and the ability to do work in the car) and travel time duration. An important insight uncovered was that the travel changes were limited and not as dramatic as expected, highlighting that the value of time impacts alone are not as representative as expected.

Keywords: Autonomous vehicles, travel behavior change, activity-travel schedules, latent class analysis

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1 INTRODUCTION

1.1 BACKGROUND AND INTRODUCTION

As automobile manufacturers continuously integrated automated services in their vehicles, driving remained a function reserved for humans, with improvements mostly directed at assisting drivers. However, considering " 65% of motor vehicle accidents are attributable to human error" [17], the focus has switched not to assisting, but rather replacing drivers. Autonomous vehicles technology emerged with promises of a transport revolution. Now, autonomous vehicles are an unavoidable reality, as most major car manufacturers have gotten involved in the race to bringing the first fully autonomous vehicle on the road [3]. Not only are car manufacturers fully committed, technology companies are as well, with the Google Waymo driverless car project being in motion since 2009, with over 8 million miles driven [68]. Forecasts estimate that within 20 years, autonomous vehicles will represent nearly 50% of vehicle sales[41], while more pessimistic estimates predict about 20% of vehicle sales by 2030 [15].

Autonomous vehicles take away, or at least reduce, driving responsibility from humans. By removing the unpredictable nature of the human factor, crashes are reduced, traffic flow is more efficient, and congestion is reduced overall [3]. AVs could also improve transport social equity, as autonomous driving allows access to mobility for people who are not able to drive safely, such as disabled people and the elderly [3]. However, these benefits are, on one hand, not guaranteed and, on the other, conducive to consequences that could essentially negate those benefits. Indeed, the expected improvement of travel efficiency and safety could increase the attractiveness of vehicle traveling. People who use public transport for the possibility to do activities may move to AVs [3]. With governments focusing on shifting modal choice from vehicles to other modes to reach sustainability goals, this may not be a desired outcome.

While the magnitude and direction of these effects are uncertain, a large problem is how they are assessed. Indeed, studies exploring the effects of autonomous vehicles have often assumed that the benefits of "hands-off" driving can be represented by a reduction in travel time penalty, as travel becomes time that can be used productively rather than lost due to driving. However, as activities on-board's influence goes beyond the travel episode itself, extending to the activity scheduling process as a whole, the limitations of the travel time penalty as a representation of this effect are significant. As models using this approach often guide AV-related policy making, it is essential to consider its limitations, and work towards more representative approaches. Building on the work of Pudāne, Rataj, Molin, *et al.*, studying the changes in daily activity schedules as a result of the services provided by autonomous vehicles is a viable alternative that does not oversimplify the complexity of activity scheduling and travel behavior in the autonomous vehicle era [64].

Thus, the focus of this research is to understand the effects of the adoption of autonomous vehicles on individual's daily activities,in order not only to identify the possible schedule rearrangements that could emerge, but also to better understand the interactions between on-board activities and other activity scheduling and travel choices.We will study changes in schedules like leaving home earlier or later, spending less time at work, or reordering activities and relate them to the travelers' characteristics, as well as AV features. The goal is to provide better understanding of not only the impacts themselves and how they manifest in travel and activity schedules, but also of the effectiveness and value of such a time-use approach in studying travel behavior. In addition, we hope to motivate the need for modeling approaches that will look beyond simple assumptions of travel time value, and rather take a person-centered approach, in which individual variations of time use constraints and preferences are considered. Insights from this research can be used as a building block for such modeling endeavors.

1.2 POLICY AND SOCIETAL RELEVANCE

A technology like autonomous vehicles is expected to have significant consequences on different levels, on transport systems all the way to health an social equity. In order to ensure safe and beneficial deployment of autonomous mobility services, significant infrastructure investments are required. Starting with the roads, basic maintenance to ensure a safe and favorable environment for autonomous vehicles in which to operate is necessary. Furthermore, as automated mobility requires significant technological infrastructure to support V2V (vehicle to vehicle) and V2I (vehicle to infrastructure) communications, necessary for fully automated vehicles to operate. In addition, as autonomous vehicles are expected to increase travel demand, as travel becomes more attractive, increasing road capacity to accommodate for the additional demand may be required [49]. Milakis, Arem, and Wee also highlighted another possible investment relating to parking. Indeed, as demand for parking may shrink, reducing parking infrastructure may be required [49].

All of these investment infrastructure and more are costly, and require thorough assessment of the benefits of the autonomous vehicle technology. However, due to the unique nature of this technology and its effects, traditional appraisal methods may not be sufficient to capture the extent of its implications. As the goal of transport projects has often been to reduce travel time, the advent of autonomous vehicles, which make travel time "useful", longer travel time may not be unattractive anymore. This puts to question the generally accepted tools of transport investment appraisal, which often focused on the reduction of travel time. But, as one of the main benefits of autonomous vehicles is productive time usage during travel, the value of shortened travel time cannot be assessed as it used to. Indeed, longer travel times are conducive to constructive time use, so traditional methods focusing on the travel time, and the "penalties" associated with longer travel times might not be able to capture the core benefits of AVs. One of the most significant benefits of autonomous vehicles is the ability to engage in activities during travel. These activities have a significant influence not only on the valuation of the trip itself, but also on the individual's activity schedule and travel choices. As defended by Pudāne, Rataj, Molin, *et al.*, simple assumptions of travel time penalty reductions may not be enough to describe the full extent of the potential impacts of autonomous vehicles, especially on-board activities on daily schedules [64].

Understanding of the effects of AVs on activity schedules is important for a broader discussion concerning the value of AVs in society and the extent to which policy makers should support it. The spectrum of possible consequences of AVs is wide, and often inconclusive, which makes meaningful discussion on how to approach regulating them difficult. Not only that, but the methods used to study these changes, with assumptions of travel time penalty reduction, may be limited in face of the prospect of autonomous vehicles. Thus, there is a discussion to be had concerning how to measure the effects of policy actions in a time with autonomous vehicles. Indeed, as suggested by Pudāne, Molin, Arentze, *et al.*, classical notions like the value of time 'will likely struggle to measure welfare effects of transport policies in the AV-era' [63]. Thus, this research orients itself to focus on the time use aspect associated with autonomous vehicles, and study how changes in daily schedule emerge as a result of how people choose to make use of their time in the vehicle. The goal is then to highlight the value of different approaches in assessing the benefits and costs of autonomous vehicles, beyond the traditionally used value of time-focused approaches.

1.3 RESEARCH DESIGN

In this section, the knowledge gaps identified from literature are introduced, and argued for, and research questions are introduced. The knowledge gaps were identified though an extensive literature review, presented in 2. The main knowledge gaps to be addressed in this research are as follows:

- We do not know how travelers would actually adapt their behavior to autonomous vehicles, and how that would translate to daily activities and travel choices.
- There remains limited understanding of how travelers actually use their time in the vehicle. We do not know well which travelers would benefit from autonomous vehicles, we do not know how individual factors like the ability to do work, and sensitivity to motion sickness influence the decision to use or not use an AV.

The first area of focus this research will explore concerns the actual changes that travelers would make as a result of having an autonomous vehicle available to them, with a focus on schedules as a whole. Literature has often assumed that activity patterns of travelers would remain the same, modeling the value of the vehicle as a reduction of the travel time dis-utility, which is essentially a proxy for the effect of productive time use in the AV, as described by Pudāne, Molin, Arentze, *et al.*[64]. Little attention in literature has been given to the potential changes in how people would schedule their day, with autonomous vehicles. Indeed, considering that the possibility of constructively making use of the travel time essentially makes it additional useful time that is not lost, the activity choices during this time become part of the overall daily scheduling process. Therefore, it is possible that individuals would bring modifications to non-travel activities along with on-board activities. Assumptions of travel time penalty do not cover these impacts, so we do not have complete understanding of the full extent of the impact of autonomous vehicles on people's traveling behavior, such as having more free time for other activities as a result of additional productivity provided by AVs.

With the schedule changes identified, the focus will move to understanding the factors associated with these changes. An example of such factors is motion sickness, but this also concerns the type of work people would do in the car, whether it is feasible, how much time pressure they are under etc. Essentially, there is little understanding of which travelers, in which situation, would actually be able to, and would want to, engage in activities in the car. As such, there is limited understanding of how travelers would use their time in an autonomous vehicles, and how their individual preferences affect it. As Childress, Nichols, Charlton, *et al.* described, models do not capture the effects of people's lifestyle choices and habits on their travel choices [11]. Additionally, when looking to the autonomous vehicles themselves, we found that there has been little done to study the value autonomous vehicles provide travelers in improving daily activity schedules. Considering the individual characteristics of travelers, each will adjust their behavior according to the benefit they receive out of autonomous vehicles. We do not exactly know what aspect of autonomous vehicle will drive travelers to change their behavior, and it would be expected that not everyone will benefit from AVs in the same way. Our contribution will address a gap identified by Childress, Nichols, Charlton, *et al.*, who suggested that future stated choice behavior surveys studying the effects of autonomous vehicles should identify the aspects of AVs that would cause people to change their behavior most (aspects like safety, ability to work) [11].

Thus, we identify the objective of this research is then to provide better understanding of the effects of autonomous vehicles on travel behavior using an approach oriented to individual activity and travel schedules. Such understanding allows not only to discuss potential impacts of autonomous vehicles starting from activity schedule changes, which literature has not addressed in depth, but also reflect on the limitations of the traditionally used travel time penalty approaches. The overarching research question that we answer in this study then is as follows:

"How is the introduction of private autonomous vehicles expected to affect the travel preferences and activity schedules of individual commuters in the Netherlands?"

Dividing this question into two main sub-questions, we can address the different layers of schedule rearrangements starting from identifying the rearrangements themselves, leading to understanding the factors influencing their emergence.

1. What types of rearrangements in travel patterns and activity schedules are expected to emerge with the introduction of autonomous vehicles?
To answer the main research question, the first step is identifying possible schedule rearrangements or changes in schedules that can emerge as a result of autonomous vehicles. As touched upon when discussing the knowledge gaps beforehand, there is limited knowledge about how travel patterns concretely change with the availability of autonomous vehicles. While this mainly concerns the first knowledge gap which focuses more on changes in activities and travel behavior, it also relates to the second one, as these changes are a direct result of how travelers choose to benefit from autonomous vehicles, and what they consider as most important and valuable in them. Nonetheless, the focus of the first sub-question is on understanding how people change the way they schedule their activities and travel and identifying all the possible (observed) changes and combinations of changes that could emerge as a result of autonomous vehicles.

2. What factors and characteristics of travelers are associated with the specific activity schedule rearrangements?
With the changes in behavior identified and classified, the next question to tackle is who makes these changes and why. This relates to the second knowledge gap, as research often ignored the impact of preferences, habits, and sensitivity to factors that are difficult to capture in models, like motion sickness and the inability to work in a car. For someone who cannot do work in their vehicle, the value of an autonomous vehicle that promises the possibility of doing work in it is limited at best. Thus, we choose to explore the effects of individual characteristics of travelers on their schedules, along with the features of autonomous vehicles that could be most valued by these travelers.

1.4 RESEARCH APPROACH

The goal of this research is to better understand how the introduction of AVs as a viable mode of transport could impact people's daily schedules. This entails studying traveler schedules with and without AVs, with knowledge of individual characteristics that could be indicators of the identified changes. Thus, a quantitative approach aimed at analyzing the transition in schedules with and without AVs is selected, with the goal of classifying schedule rearrangements, identifying the characteristics of both the travelers and autonomous vehicles that are associated with those changes.

To do so, an existing survey is used as the data source. It contains information about travel preferences and habits, in addition to socio-economic characteristics. The core task of the respondents was to design their daily schedules as they currently are, and re-design them imagining autonomous vehicles would be available to them as a travel mode. A more detailed description of the survey is in 3.1.1, along with the questions in A. Initial analysis of the data to understand it will be done, which includes cleaning, studying, and exploring the main data source, being the survey in this case. It is the first step to preparing the data for the modeling stage, which begins with descriptive statistics to understand the data set. This entails an initial cleaning of the data, by removing incomplete responses and correcting erroneous answers [1, p.340]. Following that, further analysis including identifying frequencies of responses, distributions, and correlations between the variables can be conducted, using both statistical and graphical techniques such as scatter plots and histograms [1, p.348].

The first step to answering the research question is conducting analysis of the data to identify the types of rearrangements and classify them. This will be done quantitatively by comparing differences in the activity blocks in schedules with and without AVs, mainly looking at activity durations and starting clock times and comparing how they have changed. These rearrangements can be single change, but also combinations of different changes (addition of activity, extension of another activity etc.)

With the rearrangements identified, the next step is to understand what influences them. Starting with a logistic regression, we will identify what indicators most affect whether travelers make any changes in their schedules, regardless of specific changes. Branching out to the specific changes, we will use latent class analysis to relate the changes to classes of travelers, and identify which characteristics can predict schedule rearrangements. These characteristics include socio-economic factors, travel habits and preferences, and variables relating to travelers' ability to conduct activities on board (ability to do work in the car, sensitivity to motion sickness).

While this approach is exploratory and inductive in the way the outcomes of this research are based on the analysis of the observations from the survey, it is deductive in other ways. The survey itself was constructed with certain assumptions in mind. Indeed, through exploratory research, indicators such as time pressure or travel time were assumed to have some influence on the types of rearrangements. Thus, the research is confirmatory to some extent, as it will show if these indicators are actually influential as assumed. Additionally, the full range of predictors is not explored, as it would not be possible to conduct the survey with all possible indicators. A full exploratory approach would entail an all-encompassing study of all the possible predictors of travel behavior, that is the space of indicators would be unbounded. Evidently, within the time and resource constraints of this project, this is somewhat unfeasible.

1.5 THESIS STRUCTURE

The structure of this thesis is relatively straightforward, starting from qualitative research of literature and methods. This is followed by two results chapters (Chapters 4 and5), in which quantitative data analysis and modeling will be conducted. Finally, the last two chapters will use the model and analysis results to discuss larger implications of the findings, namely on the societal and policy level. Figure 1 shows the structure of the thesis as described.

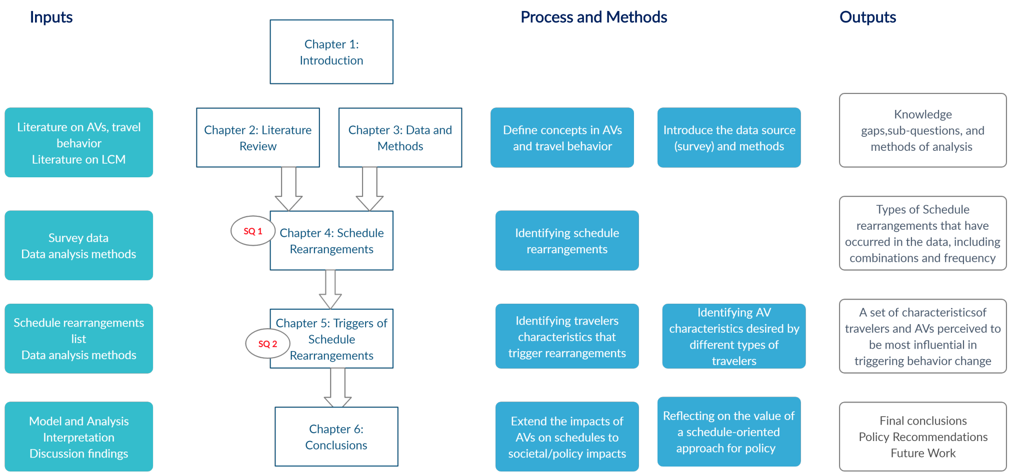

Figure 1: Thesis Structure as Research Flow Diagram

After this introduction, an extensive review of the existing literature on autonomous vehicles and evaluating existing approaches to studying the impacts of autonomous vehicles is presented in Chapter 2. From this, gaps in the knowledge and methods are identified, leading to a conceptualization of how these gaps will be addressed in this research. The data and methods to be used to do so are introduced and motivated in Chapter 3. A detailed description of the survey data, used as the data source for this research, is also provided. Moving on to the results chapter, Chapter 4 begins by introducing and classifying the different types of arrangements as found in the data. With a set of arrangements, an analysis of the causes of those arrangements begins in Chapter 5, with an initial logistic regression focusing on predicting if a change in schedules of any type would happen, followed by a deeper study into the specific changes. The second phase of Chapter 5 focuses on the type of changes identified in Chapter 4 and uses latent class models to predict which characteristics of both travelers and autonomous vehicles lead to changes in schedules. Finally, conclusions, a reflection of the policy and societal implications of the findings of this research, and future work are discussed in Chapter 6.

2 LITERATURE REVIEW

The goal of this chapter is to contextualize this research within the existing literature that studied the impacts of autonomous vehicles. To do so, we conduct a literature review introducing autonomous vehicles, their effects, as well as the concept of the value of time in 2.2.1 and 2.2.2. Following that is an introduction to different concepts of time use and activity scheduling in 2.2.3. With this, the research and scientific contributions are explained in **??**, and a conceptualization of the expected findings of this research will follow in 2.4.

2.1 SELECTION OF PAPERS

For this research, the papers selected were mainly found in top transportation research journals:

- Transportation Research Parts A, C, and E
- Transport Reviews

Search engines like Google Scholar and Science Direct, along with online databases like JSTOR were used to identify and find these papers. The search was split into themes, starting with the technology of autonomous and automated vehicles (using keywords like 'autonomous', 'self-driving, 'automated'), then followed by searching for review papers on the effects of AVs, which led to identifying the Milakis framework of effects of autonomous vehicles (descibed in 2.2.2) as a basis for organizing the effects. The journal papers studying the effects of AVs were then filtered and organized following the Milakis framework.

2.2 REVIEW

As driving became the main mode of transport around the world, technological breakthroughs brought novel features, with the latest one being self-driving vehicles, or autonomous vehicles. This review will introduce this technology, its potential impacts according to literature, as well as important concepts of time use and activity scheduling.

2.2.1 What are Autonomous Vehicles?

Levels of Automation

Autonomous vehicles are fully automated vehicles that are capable of driving safely on the road without human input [76]. That is, there is no need to have a human operating the vehicle, as it can drive itself. However, there is a distinction to be made between automated and autonomous vehicles, which are often used interchangeably. An automated vehicle can operate independently from humans, while an autonomous vehicle can make decisions under uncertain and unexpected conditions [14].

Automation in cars has begun years ago, with the introduction of tools to assist drivers, such as adaptive cruise control, which ensures a safe distance between vehicles [71] However, such technologies only provide assistance, and partial automation, as control is still within the hands of drivers. Vehicles are thus partially automated, but not autonomous, as they cannot drive completely independently. With this, it is clear that automation exists in a continuum, with different levels of automation existing between traditional human-driven vehicles and fully autonomous vehicles. A hierarchy has been developed to define the automation levels by the Society of Automotive Engineers. These levels are distinguished by the allocation of responsibility to either the driver or the system[1] in two types of features. The first type is linked to the driving tasks only, with the allocation of the *dynamic driving tasks* being the main feature.Dynamic driving tasks refer to the actions taken when driving. They are defined as operational, which includes the execution of tasks like accelerating, braking, and steering, but also monitoring the environment (other vehicles, distance...). Dynamic tasks can also be tactical, which includes responding to events, turning and using signals. Strategic tasks such as defining destinations are not included according to the SAE [70]. The second feature is defined as *driving modes*. They are specific driving scenario types that are require certain dynamic driving tasks. Examples of such modes are expressway merging, high speed cruising, low speed traffic jam [70]. They represent the capacities of the automated system to operate on the road in various situations.

In vehicles with no automation, all driving tasks are controlled by the driver, while the system has no capacity to handle any driving mode. In contrast, full automation entails no involvement from the human in driving tasks, and the full range of driving modes automated. With variations in driver involvement and driving modes available, there are several levels of automation between the two extremes.

Thus, the levels of automation as defined by the SAE are:

Table 1: Levels of Automation According to the Society of Automtive Engineers [70]

Level of automation	**Dynamic Driving Tasks**	**Driving Modes**
Level 0 - No automation	All tasks are handled by the human driver	None
Level 1 - Driver assistance	The system only assists the human driver with executing some tasks	Some driving modes
Level 2 - Partial automation	The system completely controls the execution DDT, but not the monitoring and responding to the environment	Some driving modes
Level 3 - Conditional automation	The system controls all the DDT, but the driver is expected to take control when requested to	Some driving modes
Level 4 - High automation	The system controls all the DDT	Some driving modes
Level 5 - Full automation	The system controls all the DDT	All driving modes

Making the distinction between the automation levels is important, as each level brings about a different set of effects on transport and society. Considering they are bring the highest level of automation, and thus would be the most drastic shift from traditional vehicles, level 4 and level 5 vehicle will be the focus of this research.

1 The system is the automated driving system, or the algorithm that processes the sensor data

Functions and Components of Autonomous Vehicles

In order to achieve these high levels of automation, vehicles are equipped with specific hardware and software. The hardware is in the form of sensors and actuators. The former collect data about the environment (LIDAR, cameras), track location (GPS),and the movement of the vehicle (wheel speed and angle monitors) [79]. The latter, on the other hand, are the tools with which the physical operations in the vehicle are undertaken, such as engaging the brakes [79]. On the other hand, the software is composed of artifical intelligence, and several algorithms (prediction and decision) that process the data collected and make decisions [76], [79].

The advantages of the technology lie in both elements. The sensors collect an immense amount of data of different types that may not be perceived by human senses, thanks to the high range of the radars and lidars [3]. Not only that, they also possess high processing power that allows quick data analysis and subsequently, quick reactions and decision making. With this, AVs have the potential to reduce the main causes of crashes, as they outperform humans in quick decision-making and execution [76].

These individual capabilities are only enhanced further by vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [76]. Through wireless networks, the vehicle can sense, interact, and share information with other vehicles (V2V) that may not be within the vehicle's range of sight [2]. Similarly, the vehicle can interact with the infrastructure[2], which provides the system with more data about road conditions, congestion and other information that the vehicle cannot capture with its own sensors[16]. In that way, the V2V and V2I communication can supplement the limitations of the autonomous vehicle's sensors.

Despite the evident superior performance of autonomous vehicles, the technology faces challenges in various aspects. While the vehicle could avoid accidents resulting from human error, machine errors cannot be avoided. As the fatal crash of the self-driving Tesla in 2016 has shown, 'designer errors' are a considerable challenge, as AVs can be faced with situations in which an accident is unavoidable [5]. Questions also arise over the priorities of the algorithm when faced with a situation in which it has to choose between the safety of the occupant, or the safety of others [76].

While the technology is far from substituting the human driver at the moment, it is continuously developing and will become more effective and accurate as it learns. Considering the innovative nature of autonomous vehicles and its components, introducing this technology will have unexpected consequences that must be studied and explored as thoroughly as possible.

2.2.2 Effects of Autonomous Vehicles

Considering it is a novel technology that is not yet prevalent, but promises to bring a revolution to not only transport, but to many more aspects of human life, literature of the effects of AVs is ever growing. Indeed, literature about the (potential) effects of AVs has ranged from studying impacts on land-use and urban sprawl, to energy consumption, to social inequity. The focus will remain on direct first order impacts, with travel behavior in mind.

An all encompassing review of the existing literature on the effects of AVs is Milakis et al [49], in which effects were organized over three levels depending on their order. Because of the observed focus of literature on the direct effects of autonomous vehicles on traffic and the human aspect of driving, Milakis et al focused on providing a more comprehensive view of the effects of AVs on policy and society. The paper argues that the effects of autonomous vehicles will have effects following a ripple model over three orders. The first-order effects include safety, traffic, travel costs and choices, while the second-order include vehicle ownership, land use and location choice. Finally, the third-order effects cover long-term societal concerns, such as social inequity, safety, and public health, among others [49]. These effects do not exist in isolation, rather Milakis, Arem, and Wee suggested that there are interactions between the various levels of impacts (see

2 Infrastructure refers here to road infrastructure like traffic lights and signs

figure 2 below), which makes studying them all the more challenging.

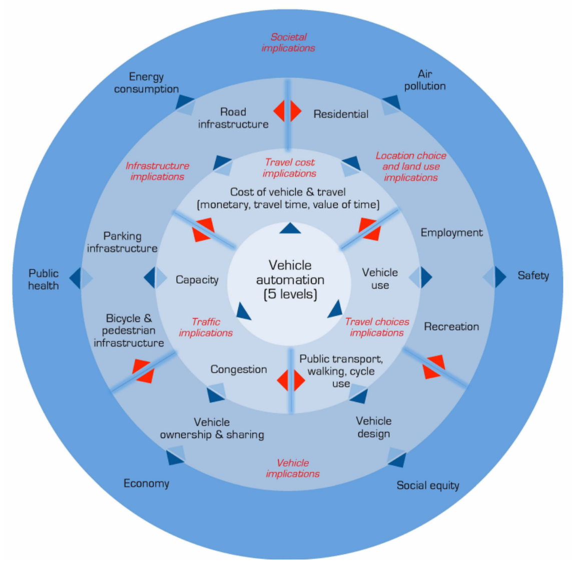

Figure 2: Ripple Effects According to the Milakis Framework [49]

Considering second and third order effects require more insight into the inter-dependencies and effects of first order effects, which are still being discussed and researched, this research will focus on adding to the literature studying first order effects of autonomous vehicles. Following the framework, the literature review will introduce the work that has been conducted on first order effects, highlighting findings and their limitations, paving the way for the contributions this thesis work aims to add to research.

Effects on Value of Travel Time

The value of travel time represents the non-monetary travel costs, which are more difficult to measure, as they relate to the time spent in the journey and the value associated with it. This metric represents the monetary value of the time spent traveling, essentially the amount of money a traveler is willing to pay for the trip, reflecting how willing they are to pay for shorter trips [9]. It is often used as input for transport demand models, and is a crucial factor in transport investment appraisal.

Overall, research claims that the value of travel time would decrease as a result of autonomous vehicles because of the improvement in safety, comfort, and the ability to engage in activities [49] [13][87]. Specifically focusing on the impacts of multitasking during travel, initial research on the impacts of on-board activities focused on various factors affected by different types of activities. One of the main effects of travel multitasking is productive time use, which allows travelers the possibility to transfer activities from another time, effectively providing them with more useful time [34]. This was supported by Pawlak, Polak, and Sivakumar, who found that productivity increased when travel conditions were conducive for work [60]. With increased productivity, or more enjoyable trips, travel time is seen less as lost time. According to Lyons and Urry, a consequence would be that travelers are less willing to spend money to avoid long trips, thus reducing their value of travel time [43].

While literature has suggested that activities and multi-tasking on board have an effect on the value of travel time, empirical research determining the magnitude of this effect is somewhat scarce. One of the earliest works attempting to do this is that of Ettema and Verschuren who, through a stated choice experiment, studied the effect of multi-tasking with different types of activities and polychronicity on the VOT [20]. While it was found that monochronic travelers (who do not conduct any activity during travel) display a higher value of time than travelers who do engage in activities, the authors suggested that individual factors (time pressure, purpose of trip etc.) also contribute to this effect [21]. Kouwenhoven and Jong corroborates the hypothesis and found that public transport users able to spend their time in a useful way had a lower value of travel time, but with considerable dependence on comfort and availability of ICT devices [33]. With the goal of uncovering the effects of activities alone without the confounded influence of in-group differences, Molin, Adjenughwure, Bruyn, *et al.* conducted a stated preference survey in an activity and non-activity context, which led to another confirmation of the hypothesis that the possibility of conducting activities on board does reduce the value of time [54]. While these findings were researched for public transport, they remain valuable in the context of autonomous vehicles. However, the uncertainty surrounding how travelers will experience AV travel brings to question the validity of the expected reduction in value of travel time. Research like Yap, Correia, and Arem hints that travelers may not perceive the benefits of on-board activities and would rather pay more to reduce their travel time in an AV, putting to the test the hypothesis that improved productivity and enjoyment in the car reduces the value of travel time [86]. Considering the importance of the value of time as evidence in transport policy, assuming the value of travel time will decrease due to AVs is not sufficient. Addressing this, Correia, Looff, Cranenburgh, *et al.* investigated the value of travel time of private AV users specifically, finding that it does indeed decrease when travelers are able to conduct work activities [13].

While this is consistent with existing research, ([22],[81]), there is an argument for there to be more nuance in assuming how travelers would use their travel time, and thus in the assumed reduction in the value of travel time. Singleton argues that the effect of AVs in reducing the value of travel time is not as large as expected, as travelers may not “necessarily use their newly available travel time for productive in-vehicle activities” [69]. Correia, Looff, Cranenburgh, *et al.* may be correct in expecting a reduction of travel time associated with the possibility of conducting work activities, but it is important to consider that some jobs cannot be conducted in a moving vehicle, be it due to the nature of the job itself, or other difficulties. One of them is motion sickness, which has often been undermined in autonomous vehicles studies, despite being inevitable in every current scenario of AVs [18]. Motion sickness, as part of the comfort factor, is only one of multiple factors that have an effect on whether or not travelers engage in activities on-board. Keseru and Macharis identified several of them (trip characteristics, socio-demographics...), distinguishing different levels of significance, and acknowledging that just removing the driving responsibility and allowing the possibility to conduct activities is not sufficient to influence travel time use, and thus the value of travel time [30].

Travel Time Penalty in Studies of Autonomous Vehicles Effects

Despite the uncertain value of travel time change as a result of autonomous vehicles, several modeling studies have used the expected reduction as a basis to represent the influence of on-board multitasking. The reduced value of time is represented as a lower travel time penalty in modeling studies.

Many modeling studies addressed the effects of autonomous vehicles on travel behavior, focusing on the changes in vehicle-miles traveled. Most studies agree that the VMT would increase as a result of AVs, in varying degrees [11][4] [34]. However, these modeling studies all assume that the effect of productive multitasking on-board can be represented by a single reduction in the value of travel time, though different scenarios are considered. The expected productivity on-board is not guaranteed, as argued by Singleton, who reported that passive non-productive activities are most common in transit and car passenger commuters [84]. Further, using a simplified value of travel time reduction does not consider the variations in value of time changes with respect to specific multitasking activities. Indeed, as identified by Correia, Looff, Cranenburgh, *et al.*, leisure and work activities during travel influence the value of travel time differently. As such, the value of the activities themselves, which would vary between individuals, depending on their personal characteristics, needs and preferences, is not considered as part of the travel time valuation process.

Furthermore, changes in activities during travel are tightly linked to the rest of the activities. As studies of the impact of ICT on activity-travel patterns have highlighted, changes in these patterns are complex, involving various elements of activity substitution (transfer of activities), complementarity, and modification [53] [36]. Indeed, tele-activities could serve as replacement for physical activities (substitution), or provide more space for new activities (complementarity), or be part of a series of travel-activity modifications. We can expect that AV-driven travel multitasking would influence activity-travel patterns in such complex fashion, as they provide additional useful time for activities in ways similar to what ICT facilitation provides. These complex inter-dependencies between the different elements of activity and travel cannot be captured through the travel time penalty currently used in models.

To summarize, as travel time in the AV era becomes part of the overall activity scheduling process, the way individuals make use of that time is not independent from other activities. Thus, limiting the influence of autonomous vehicles to the travel time period only by using value of travel time reduction constrains the perspective, and allows limited understanding of the variety in activity and travel changes with the additional time available. As such, we propose an approach focusing on exploring the possible effects of autonomous vehicles on activity-travel patterns by studying activity schedules.

2.2.3 Concepts of Activity Scheduling

With the promise of activity facilitation during travel, conscious choices aimed at saving time or freeing up time for different usage outside of travel are expected. Indeed, as the travel time becomes "useful time", the process of choosing how to use that time is essentially part of the overall activity-time allocation or scheduling process. This process depends on many different factors, relating to location and time restrictions, but also the ability to do an activity, or personal preferences. Thus, using theories of time use and activity scheduling, we can anticipate what changes could be observed in the data. In this section, we will introduce various theories of time allocation, with examples of studies that have identified ways in which individuals schedule their activities.

Time-geography and Time-Space Constraints

An important first theory to consider when discussing how time is allocated to activities is time-geography, and the concept and space-time constraints as a driving factor of time use. Hägerstrand defined this framework to study how events occur, identifying that individuals act and schedule events within certain physical and temporal constraints. Hägerstrand categorized time-space constraint in three types:

- Capability constraints, related to limitations in instruments, cognition, or physiology of the individual and their environment.
- Coupling constraints, related to the need of individuals to join other individuals, tools, and materials in order to produce, consume, and transact at specific times and locations. For instance, certain work meetings can only be had with a specific set of people, during a specific period (a set time during the work day), in a specific location (a meeting room).
- Authority constraints, are the laws, rules and norms regulating the access to space-times. For instance, opening hours of shops limit the time period in which individuals can visit.

[26]

These constraints limit the activities individuals can participate in, and guide their activity time allocation. In the context of autonomous vehicles, we think that these constraints remain relevant, though the technology relaxes some of them. While there is no research studying the specific impacts of autonomous vehicles on these constraints, inferrences can be made from studies that have explored the influence of ICT resources. Indeed, Schwanen and Kwan showed that ICT resources provide more activity spatial flexibility to individuals by allowing different ways of engaging in activities using technology [66]. For instance, when meetings could only be held in person, ICT tools provide the possibility to hold meetings virtually, thus eliminating the spatial constraint, and freeing up time for the individual (for instance, the trip to the location would not be necessary anymore). Furthermore, Schwanen and Kwan emphasized on the ability to multitask (engaging in multiple activities at the same time) as a bi-product of the use of mobile phones [66]. Considering that autonomous vehicles promise high flexibility and multitasking capabilities, through removing the driving responsibility from the hands of the individual and allowing the use of ICT tools, we can infer that autonomous vehicles will have a similar relaxing effect on spatial constraints. This would translate into an extension of the range of activities that can be conducted in the car, with activities that could not be done previously as a driver, such as reading or sleeping, becoming possible. Thus, with improved connectivity and multitasking capacities, autonomous vehicles reduce the effect of capability and coupling constraints. While authority constraints can be reduced, with online shopping being an example of ICT improving the temporal flexibility of the shopping activity, several aspects of such constraints cannot be removed completely with the introduction of autonomous vehicles.

Activity Scheduling

Building on the constraints introduced above, we can infer that activities differ in how critical their constraints are on the three levels. As a result, the choice of engaging in an activity is highly dependent on the characteristics of the activity. Distinguishing between productivity and expressiveness in activities, Ås has introduced a typology of time use. Indeed, he indicated that some activities are instrumental and productive, with a distinction between paid work or education, which he called contracted time, and regular unpaid work like shopping and household chores, which he called committed time. Ås considered them instruments to achieving the needs of the individual. On the other hand, expressive activities are those aimed at satisfying physiological needs, like eating and sleeping (necessary time), and those aimed at satisfying acquired needs, like leisure activities (free time) [89].

Combining this with the aforementioned spatio-temporal constraints, it is clear that necessary time offers little flexibility, as physiological needs like eating and sleep cannot be replaced or transferred from a time to another easily, as they occur regularly and often take priority over all other activities. In agreement, Ås suggests that there is little freedom in necessary time, as sleeping and eating always happen, often at the same time everyday, with little variation in duration [89]. However, in the case that autonomous vehicles are available, such activities can be transferred to the travel episode in principle, as the spatial and capability constraints are removed (the individual is not constrained by having to drive). Evidently, this does not mean that travelers will do so, as it requires a dramatic shift in schedules, as well as fragmentation (in the case of sleep), which are now designed with necessary activities happening at set times.

While contracted time can be slightly more flexible, it remains highly limited, as the authority constraints in the form of contractual agreements and work regulations limits the extent to which and individual can modify the work activity (in duration, start/end time). Coupling constraints are also powerful in this instance, as some occupations depend on interactions with other people, and resources that may not be at the disposal of the individual at all times. However, as mentioned beforehand, ICT tools in combination with high multitasking capabilities in autonomous vehicles can provide the necessary environment to transfer these activities to travel episodes, while temporal constraints remain difficult to modify.

Committed time involves more choice from the individual, as they can choose when to do these tasks (when to go shopping, when to clean the house etc), but Ås mentions that this freedom is merely a sort of postponement, unless they are transferred to another person [89].

Indeed, while the authority constraints in the traditional sense (laws) are not present, softer constraints are, such as the need for essential supplies, which requires shopping, or the need to live in a clean environment, which pushes the person to do cleaning and household chores. In the context of autonomous vehicles, some of these activities, like cleaning, are considerably limited by their dependence on location, so they are less likely to be done in the car.

Finally, there remains free time, which has the highest flexibility and freedom, as hardly any constraints apply. Free time here refers to any activity that is done for the purpose of enjoyment and leisure. Leisure activities are generally easier to reschedule or replace, though there remains limitations of location, resources and the need for interactions (sports practice for instance). Therefore, when looking at the possible exchanges in activity order and occurrences, committed and free time have the greatest flexibility. However, in the context of autonomous vehicles, we observe that individuals can engage in work activities, which fall under contracted time, in the car thanks to ICT tools. While this is considerably limited by the type of work and resources available to the person, it is expected that autonomous vehicles increase the overall flexibility of contracted time, be it for work or study. On the other hand, committed time is just as limited by the resources needed and its reliance on the location. For instance, it is not possible for an individual to do all of their household chores in a vehicle, so the flexibility that Ås identified is significantly tied to location. Thus, we expect that fewer activities may be transferred to travel episodes, but rearrangements outside trips are be possible, like reordering post-work home activities, or directly substituting them with pre-work home activities. As for leisure activities, we expect that they can be a significant contributor in the rearrangements, as they can be conducted in the car, assuming the necessary resources are available, but also be moved around in non-travel periods.

Activity Scheduling in Practice

Allocation of time is a complex process that is influenced by multiple factors, the type of activity (or time) as shown by Ås, or the constraints of time and space that affect utilities as theorized by Hägerstrand. The question that arises is then how this translates in practice. Clark and Doherty conducted an in-depth study of the decision process individuals go through as they make modifications in their activity schedules [12]. The authors conducted multiple surveys tracking activity rescheduling in normal days. Starting from the belief that the focus of existing models on conflict resolution as the sole rescheduling strategy is limited at best, the authors suggest that rescheduling decisions happen because of different changes in activity attributes (location, type, people involved). With this, they explore the various rescheduling decisions, and how sociodemographic and activity variables affect them.
The activity changes most commonly observed are adding or deleting an activity, modifying the start or end time of an activity, or modifying both.
Clark and Doherty identified various reasons that drive the possible changes in activities, going beyond the generally assumed scheduling and conflict [12]. They are as follows:

- decisions made by or in concertation with other people, which is a manifestation of the coupling constraints
- conflict and scheduling issues, trying to fit multiple activities in a limited time period.
- personal need, the individual's belief in the necessity of doing an activity at a specific time, with limited alternatives
- personal choice, which reflects the individual's preferences, often in reaction to ongoing events or plans.
- flexibility, uncertainty of timing or location of an activity
- outside factors, which are events outside the control of the individual, such as the weather, opening hours...

- convenience, which the authors describe as a desire to improve the efficiency of the scheduling process by way of multitasking and trip chaining.

The authors found that "personal needs" is more likely to cause addition of activities, while conflict issues would lead to modifications in start and end time and deletion of activities. Interpersonal factors was found to lead to activity additions and modifications of start time. These modifications are made more unconsciously compared with additions and deletions. Linking this research with the space-time constraints, Clark and Doherty found that coupling constraints rarely have influence when the reasons for change are conflict and scheduling issues and personal needs, as they often involve decisions being made alone [12]. While socio-demographic characteristics were found to have limited impact on the rescheduling decisions, the activity type and the duration of the rescheduled activity were found to have considerable influence.

Compressed Working week

Considering autonomous vehicles would have effects somewhat uncertain on the flexibility of activities (especially in location constraints) and individual preferences, different rescheduling decisions may emerge. Another study that explored how people adapt their schedules as a result of some change in the characteristics of some activity is the experiment of the compressed 4 day working week in the Philippines conducted by Sundo and Fujii [75]. In this,workers had their working day extended by 2 hours, which then allowed for the working week to be 4 days as opposed to 5. This applied to a few companies, with the day off being Friday for some, and Monday for others. The authors found that activity-travel patterns were be significantly impacted, with considerable changes in departure times. Indeed, workers left their homes in the morning an hour earlier, and left their workplace an hour later. This was associated with a decrease in commute time, which could possibly be attributed moving the time of travel to a time with lower traffic demand.

As for activities, it was found that workers found allocating time for activities more difficult with the extended working day, which is consistent with the typology of time as introduced by Ås, in which contracted time takes precedence over committed and free time [75]. Both pre-work and pre-sleep household activities were reduced, and while a reduction in sleeping time was observed on average, it was the least significant, which indicates a certain difficulty, and probably additional associated costs, in modifying sleeping duration. The reduction is mostly due to the earlier waking up time.

Overall, the authors found that activity and travel patterns are determined by timing just as much as they are by activity–time allocation patterns [75]. Furthermore, there may be resistance in changing certain activities, which could be associated with variations in marginal utility of activities and associated (non-monetary) costs.

AV-driven changes in Georgia

Closer to our topic of research, Kim, Mokhtarian, and Circella researched how people expect their activity-travel patterns to change as a result of autonomous vehicles in Georgia [31]. The authors identified sixteen possible activity changes, both stationary and on-board, and four factors describing different characteristics of travel and activities (distance, frequency, flexibility, long-distance/leisure). Distance relates to the inclination to travel longer distances, frequency refers to the inclination to travel more frequently (increased number of trips), time flexibility relates to the tendency to change time use, while long distance/leisure describes the inclination towards making specific long distance or leisure trips more often. With this, the respondents were grouped based on their expectations regarding their AV-prompted activity changes, i.e. how likely they are to make each of the 16 changes, with each change associated with one of the factors. While half of the cases fell under the clusters **no change** and **change unlikely**, there remains a significant portion of the sample that was found to be enthusiastic about AV-driven changes. The most significant clusters that do include changes are long distance trips for leisure, longer trips in general, more travel, time flexibility & more leisure/long distance.

The authors found that autonomous vehicles have a more considerable influence on travel distance than on travel frequency, that is people expect they would travel to longer distances rather than add individual trips to their schedules. However, this effect is not uniform across all the sample, as longer distance travel was observed in regular daily trips for some travelers, but for others only in occasional long distance trips. However, it was clear that the activity changes were more modest than anticipated, with especially low expectations from respondents of changes in time flexibility, which could indicate that productive use of the newly freed up time (in vehicle and out) may not be very significant. Though, younger and more tech-savvy individuals could make more use of the time on-board for productive activities.

This approach provides an alternative to exploring changes in activity patterns in the autonomous vehicle era, acknowledging that characterizing behavioral changes is a complex process, one that received little attention by researchers. Our research would aim to complement this study. Kim, Mokhtarian, and Circella did not consider the interactions between the various activities, both on-board and stationary when anticipating the changes in schedules. More work on-board is only associated with a decrease in stationary work activities, but the effect could go even further, with for instance an increase in free time as a result of the reduction of the stationary work duration. Thus, our research will build on this by exploring a wider range of changes and combinations of changes in activity time allocation.

2.3 RESEARCH CONTRIBUTIONS

As identified in the review, research exploring the impacts of autonomous vehicles has mostly used a travel time penalty to represent the influence of on-board activity multitasking. As this approach is being challenged, researchers have proposed alternative approaches focusing on activities. Methods like focus groups ([64]) and surveys ([31]) specifically explored changes to activities as a result of autonomous vehicles. However, the former does not have a quantitative basis to confirm its findings, while the latter has a limited scope of activity changes. Our research aims to provide a quantitative study of travel behavior changes, focusing on activity patterns.

As argued, the associations between on-board activities and activities outside travel (stationary activities) are significant, and should not be overlooked when exploring potential activity changes. This thesis aims to be another contribution to the ever growing research exploring the impacts on autonomous vehicles on travel behavior, focusing on activity-travel schedules. The addition we bring is an in-depth quantitative exploration of the rearrangements considering the different interactions between activities during and outside of travel episodes, as well as with the travel decisions themselves.

The general aim of this study is to explore potential changes (and combination of changes) in activity schedules, and examine whether or not socio-economic and personal characteristics contribute to these changes. The starting point for this study is a survey that was conducted by Baiba Pudane, which asked of respondents to provide their regular daily schedule with their preferred mode of transport, and imagine what the schedule would look like with an autonomous vehicle as their only mode of transport. In addition to these schedules, the survey contains information about individuals' socio-economic, travel and personal characteristics (more detailed description in chapter 3). Using this data, this research aims to explore:

- The different potential activity and travel changes that emerge in the schedules by comparing durations and frequencies of the different types of activities and trips
- The potential factors influencing the occurrence of schedule changes using a logistic regression
- Possible classifications of individuals based on their schedule changes and their personal characteristics using latent class cluster analysis

The results would contribute with quantitative findings and analysis to the growing field of research exploring the impacts on autonomous vehicles on travel behavior.

2.4 CONCEPTUALIZATION

While we now have a clearer idea of how literature has uncovered on the different types and magnitudes of impacts expected as a result of autonomous vehicles, and a set of knowledge gaps identified, uncertainties remain. We still do not know how travelers would adapt their behavior, observed through daily schedules, after the introduction of autonomous vehicles.

While we now have a clearer idea of how literature has uncovered on the different types and magnitudes of impacts expected as a result of autonomous vehicles, and a set of knowledge gaps identified, uncertainties remain. We still do not know how travelers would adapt their behavior, observed through daily schedules, after the introduction of autonomous vehicles.

The first question to look at is what changes in daily schedules emerge as a result of autonomous vehicles. This entails an initial exploration of whether changes have been made or not, followed by a deeper look at the schedules that have been changed and classifying the changes. This will be done through a comparison of the schedules pre and post- autonomous vehicles. In conventional vehicle travel, the travel activity and any other activity are generally distinct, and do not happen at the same time. In the autonomous vehicle-era, that distinction becomes blurred, as non-travel activities can be conducted during trips, thus having an impact on other travel and non-travel activities. Thus, in this research, the initial step in identifying the schedule rearrangements is classifying them into activity rearrangements, travel rearrangements, or a combination of the two types of rearrangements.

Table 2: Some Types of Schedule Rearrangements

Activity Rearrangements	**Travel Rearrangements**
Addition/removal of activities	More/Less trips
Change in order of activities	Changes in departure time
Change in duration of activities	

Once the changes are identified and classified into activity and travel rearrangements, the focus moves to understanding who makes these changes, and why they are made.

A considerable factor in the choice to use autonomous vehicles, and in how the travelers adapt their behavior relies on the technology available, but mostly on the individual traveler characteristics and perceptions. While the survey provides data on the socio-economic features of travelers, data on their perceptions and attitudes towards autonomous vehicles is limited to a insights on their views of new technology and how much they are considering using an autonomous vehicle. With this limitation, we can only explore theoretically the effect of individual perception of the value of autonomous vehicles on the changes in schedules. The focus of the quantitative analysis remains on relating the individual travelers' characteristics, socio-economic factors and travel preferences to schedule changes.

The next question to tackle is who makes these changes and why. While all indicators will be considered, there are some that we consider will be influential on travel and activity schedules. We believe that some public transport users would make changes to their schedules, but we do expect the majority will not, as the additional benefits of autonomous vehicles may not be much more valuable than their public transport experience. Vehicle and bicycle users have more to gain from the reduced responsibility during travel, so we believe that they would engage in activities on-board, which may impact the rest of their day. Work activities in the car constitute an important element of on-board activities, but they depend on many factors like the type of work, and the ability to do work in the car (also related to motion sickness and comfort levels).

Considering over 90% of the respondents in this survey are employed, we expect the ability to do work in the car, time pressure, and the type of work to be influential factors. Considering autonomous vehicles are a technology that is not available to the public now, we think that the existing perception people have of it, and the extent to which they would be willing to use it are influential indicators. Respondents who are open to trying new technologies and who would consider buying or using an AV would be more likely to make use of its features, which could translate to schedule changes.

2.4.1 Typology of rearrangements

With this mind, we can begin to think of the possible rearrangements that could emerge in our subsequent analysis.

We believe that the possibility of engaging in activities during travel will give people more choices in how they allocate time. As introduced beforehand, there are different theories outlining how people allocate time. In the case of autonomous vehicles, activities can be integrated in the schedule by substitution, as in an activity is moved from a stationary episode to a travel episode.

The first type of rearrangement to consider is one with no change. Indeed, there is a possibility that individuals do not engage in any activity on-board, rather choosing to enjoy the experience of riding an autonomous vehicle (considered to be pleasant and comfortable) without expecting the time has to be used for productive purposes. As such, there would be no subsequent change on the activity schedule.

In a similar vein, a possible rearrangement is one that stems not from the addition of activities on-board, but rather from the positive experience of riding in an autonomous vehicle. For instance, a traveler can have such a pleasant and relaxing ride on an autonomous vehicle that they no longer feel tired once they reach their home, so they have free time to allocate to other activities.

Another factor influencing the activity schedule is the need for new activities, which can be satisfied in the newly freed up travel time. Indeed, an arrangement type of rearrangement that can emerge is one in which an activity that did not exist in the original schedule is added to the travel episode. On one hand, this addition can lead to no change in the schedule if the aim was only to satisfy that single activity. Such rearrangement could occur because the time outside travel was not sufficient to include this activity, so the autonomous vehicle provides additional time during travel that can be used. These activities could be one-off activities that do not happen regularly, but they could also be regular activities with relatively low importance, stemming out of personal preference of the individual, not necessarily out of necessity. An example provided by one of the respondents in [64] was doing something they never have time for, like doing karaoke in the car.
On the other hand, the addition of a new activity in the travel episode can lead to changes in the schedule.

The final type of rearrangement is one in which the interaction between on-board and stationary activities is critical. An important concept here is that of substitution, which is exemplified by transferring an activity from a certain time in the schedule to a travel period, thus freeing up the original time slot. While this direct substitution can occur with no other change, this single change can lead to several others. This effect is the saved time effect, which allows for changes like adding new activities, removing others, or reordering activities to occur, within the space-time constraints introduced by Hägerstrand.

With a clear idea of how changes in activity schedules can be made, we can anticipate different types of changes that could emerge, from which combinations can create types of rearrangements. We distinguish between changes in on-board activities, activity schedules, and in travel characteristics.

Expected changes on-board

Starting with on-board changes, it is important to consider the feasibility of activities, as not all activities can be conducted in the vehicle, and many require preparation or resources that must be thought of beforehand.

When it comes to transferring existing activities to the travel episode, the flexibility and the nature of the activities is just as influential as their feasibility. Indeed, as introduced earlier in the typology of time by Ås, the different types of time differ considerably in flexibility, which means that some are more difficult to change than others. According to Ås, due to its rigid nature and high priority, necessary time would be most difficult to change. Therefore, we expect that there would not be many such activities transferred to the travel period. For instance, sleep generally occurs in one block, at roughly the same time everyday, so we expect that there would not be many instances of sleep on-board, bar some special cases, like long distance travel. This was exemplified in the compressed working week experiment in [75], in which the reduction of sleep duration was the least significant, a sign of higher resistance to change with such necessary activities.

Eating on the other hand is slightly more flexible, as breakfast can be easily transferred to the morning travel period.

Contracted time is considerably more flexible, and possibilities of transferring work or study activities to be on-board are higher than those of sleep, in parts thanks to the availability of ICT resources in the vehicle. Pudāne, Rataj, Molin, *et al.* considered work and study as high priority activities, and added the influence of time pressure in the decision to engage in such activities on-board [64].

While there are doubts over the extent to which travelers would use the traveling time on autonomous vehicles productively (as Singleton points out), there is evidence that a portion of the population would make use of that time. In a stated preference survey, Wadud and Huda found that working and studying were the second most popular activities during outbound commute or business trips [82]. With this, we expect that work activities are likely to be transferred to the travel period, but for certain travelers more than others, and within the constraints of feasibility and facilitation. We expect that employed, tech savvy travelers who experience high levels of time pressure would be likely to use the time in the autonomous vehicle to do work.

Activities that fall under committed time are shopping, household chores, which are often location specific and cannot be transferred to the vehicle. There are some exceptions, like online shopping, which can be conducted in the vehicle, assuming the required ICT resources are available, but most activities are limited by those constraints and are not feasible in the vehicle. Thus, we expect that there would not be many such activities conducted on-board.

Finally, activities that fall under free time, like leisure and relaxing, are the most flexible, and the most likely to be done in the vehicle. While this is in part because they require little preparation or resources, the effect of removing the driving responsibility from the individual is also important. Indeed, for many, driving is a stressful endeavor, and the removal of this responsibility in and of itself can improve the well-being fo the rider, and reduce the negative utility associated with driving [69]. With this, we can expect that travelers may take the newly freed up time to relax and enjoy a trip with reduced stress. This is supported by Wadud and Huda, who found that travelers often "switch-off", especially in home-bound trips, and engage in relaxed activities that do not require intense attention [82]. Further, in public transport, the most common activities are passive like relaxing, watching people,looking outside the window, listening to music etc., so we expect this could translate to autonomous vehicles as well [69].

In summary, the on-board changes that we anticipate are:

- No activity on-board
- Increase in duration of work activities on-board
- Increase in duration of meals on-board
- Increase in leisure/free time activities on-board

Expected changes at the level of stationary activities

Non-travel activities may be influenced by the addition of on-board activities, or from the positive experience of riding an autonomous vehicle, in different ways. While we expect that direct substitution may be prevalent, that is a non-travel activity is transferred to the travel episode, more complex complementary modifications may emerge. With the rise in work activities on-board, we expect that this comes with a reduction in stationary work activities, as direct substitution is more likely there. Similarly to meals, we expect that travelers who would have meals on-board would not eat the same meals outside of the vehicle, so a reduction of meals outside is likely. We believe that the time on-board, if used, will be used to relieve time pressure, so we expect that there will be more free time available to individuals to engage in leisure and spare time activities outside the vehicle that they did not originally have time for. Thus, we expect that new leisure activities may be added, or that existing such activities will be extended.

All in all, we expect the following changes to emerge:

- Little to no change
- Reduction in stationary work duration
- Reduction in meal durations
- Increase in spare time
- Addition of activities (mostly leisure)

Expected changes at the level of travel

Departure time to work would be changed, sometimes in parallel with departure time from work. Assuming that the total duration of the work activity would stay constant, a delay in departure time to work is expected with a possible combination with an earlier departure time from the workplace, and work on-board in both trips. The opposite can be observed as well, with earlier morning departure times and delayed departure times from work, with some activities transferred to the travel episodes. Additionally, a change in departure time could also occur independently from any activity change, especially in return trips which were found to be used for relaxing [82].

As we assume that autonomous vehicles provide a positive utility, extrinsic through allowing multitasking, but also intrinsic by providing comfort,we expect that the attractiveness of long distance travel will increase, not only in daily life but also in occasional out of city trips.

Thus, we expect the following changes could occur, independently or in combination with other changes:

- Travel to work at a different time (earlier/later)
- Travel home earlier
- Travel longer distances

While the times of travel can be explored, the data set available to us does not allow us to explore the trip distances or durations, as the respondents were only able to choose trips with fixed travel durations.

2.4.2 Factors Associated with Schedule Rearrangements

The exploration of the factors that could have an influence on schedule rearrangements is split into two parts: an initial study of the possible predictors of the occurrence of different schedule changes, followed by a deeper study into the factors associated with specific schedule changes.

With a better understanding of the rearrangements that emerge in the autonomous vehicle schedules, the question to address next is what drives those changes. More specifically, the questions to be answered in this section are as follows:

- What individual attributes are most significant predictors of activity-travel schedule changes?
- How do these attributes influence the occurrence of activity-travel schedule changes?

The first question to address is how to represent the schedule rearrangements. As identified in the previous section, the types of changes relate to activities on one hand, both on-board and stationary, and travel on the other. The ways in which to study these changes vary, but we choose to first explore what drives the occurrence of changes in general, before exploring the specific changes in more details using latent class clustering. As such, three binary variables, describing the occurrence of each type of change, are created.

We believe that the schedule changes driven by autonomous vehicles are in part influenced by the individuals' unique characteristics. In the context of this research, this includes three layers of influence, with varying degrees of stability and objectivity of the variables. The first type of indicators is the socio-economic factors, which describe the gender, age, income, education levels and other objective characteristics of the respondents. The second type of indicators represents the features of travel that correspond to the respondents, such as their preferred mode of transport, the frequency of their travel, and the range of single commute trip time. Finally, the next set of indicators describes different personal characteristics that were believed to influence the individuals' perception of autonomous vehicles and the value they can bring. These include motion sickness, exposure to new technologies, and the ability to do work tasks during travel. All three describe different elements that could encourage or discourage people from using an autonomous vehicle: comfort, affinity and openness to try innovative technologies, and the possibility of remote work.

With that in mind, we map out a conceptual model of the effects and interactions we assume and expect to uncover (see figure 3).

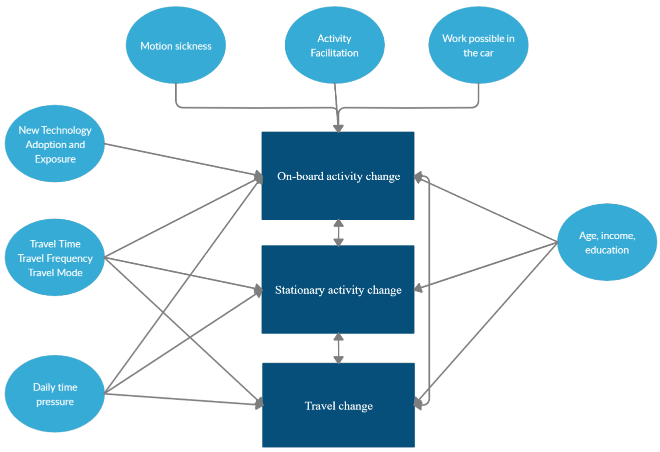

Figure 3: Detailed Regression Conceptual Model

Based on existing literature studying travel time multitasking ([34], [31], [81]), we expect that socio-economic factors like age, gender, education and income would influence in some way the expected schedule changes of travelers, especially as they relate to other possibly influential characteristics like exposure to technologies and autonomous vehicle knowledge. As per Kim, Mokhtarian, and Circella, younger and higher income individuals would be likely to make more travel related activity changes, while also considering experience with technology as an important factor [31]. Though the type of work of the individual may be influential as well, especially as it affects the flexibility of remote work tasks, we believe this effect would be captured through income, as professions with higher salaries would provide more opportunities for remote work. Similarly, the number of children living in the household could possibly influence the stationary activity changes, as literature has identified that parents tend to have significant fragmentation of their daily activities[3] [48]. Nonetheless, we believe the responsibility of caring for children would bring more time pressure to individuals, thus, the effect of the household size and characteristics would be captured through the influence of time pressure.

The circumstances of travel are also expected to significantly shape the decision to multitask on-board, as well as to modify travel patterns. The most evidently significant factor would be travel time, as we expect the commute duration would limit or expand the possibilities for activities on-board. If the travel duration is generally short, the value of engaging in productive activities may be lower than in longer trips. Further, we would expect the travel mode to have some influence on on-board changes, as public transport users may be more open to travel multitasking, while car drivers may want to travel without the stress of the driving responsibility.

We expect time pressure to have some influence on travel as well as on-board activities, as identified by Pudāne, Rataj, Molin, *et al.* [64]. Indeed, we expect that travelers who experience pressure because of limited time available for the activities they want to engage in would be more open to using the travel time in an AV constructively. As such, they would also be open to restructuring their stationary activities to some extent so long as it helped reduce pressure.

However, we understand that the need to engage in activities during travel is not sufficient to influence such changes, as other attributes may be not provide the environment needed. Two variables that we expect to play a significant in limiting on-board changes are motion sickness and the ability to do work in the car. Starting with the former, literature has shown that it has a negative effect on the levels of comfort and facilitation, which passengers would feel at lower rates of acceleration than if they were driving [18]. As a result, some activities may not be feasible or comfortable to do during travel, especially if they already have experience suffering from motion sickness. As such, we expect that motion sickness would make engaging in activities during travel less attractive. In combination with this, the activity facilitation indicator, ideal or partial, may also enhance the effect of motion sickness, as individuals with partial facilitation and occasional experience with motion sickness may believe they would feel discomfort and would not be able to engage in activities during travel. As such, we expect the two variables would have a joint effect on the decision to make on-board changes. The next important factor to consider is the ability to do work in the car. Considering work is one of the most widely common activities during travel in AV schedules, we believe that the inability to engage in work activities remotely would be a significant limiting factor in the decision to work in the car. Though it is important to remember that other activities, such as spare time and meals, have been observed during travel, so the influence of this variable may not be clear and straightforward here.

Moving on to the next stage, the main question that it aims to answer is *What factors and characteristics of travelers are associated with the specific activity schedule rearrangements?*. To do so, we explore the following questions:

- How can the respondents be clustered in homogeneous clusters based on individual rearrangements, and combinations of rearrangements?
- How do single rearrangements interact in a schedule?
- How do individual characteristics influence rearrangements?

This stage of this research is highly exploratory, though there are certain expectations stemming from the quantitative data analysis conducted in the classification stage that may or may not be confirmed here. The first step is to generate latent class cluster models for the single rearrangements and their combinations, without including the socio-economic and individual characteristics of the respondents. The goal is to understand how the single rearrangements interact, that is how the addition of, for instance, the travel departure time indicators changes the distribution of clusters with only the duration change indicators. With a better understanding

3 fragmentation represents the sequencing of multiple short activities or trips[48]

of which combinations of rearrangements exist, and how each of the individual rearrangements contribute to them, the next step is to introduce the individual and socio-economic characteristics to identify the different types of people in the clusters, and understand how those characteristics contribute to the specific rearrangements. As the regression models have shown that the socio-economic factors, and to a lesser extent, the subjective personal characteristics, contribute little in predicting the decision to make a change in schedule, of any of the three types, we expect that the interactions between the different individual rearrangements are significant.

We expect several interactions between travel and stationary activities to emerge. Starting from changes in travel departure time, we expect that earlier travel to work leads to less time available for pre-work activities (getting ready and meal), as well as sleep. Assuming the duration of sleep is the same, an earlier departure time to work could mean waking up earlier, but also sleeping earlier, which could then reduce the duration of pre-sleep activities (mostly spare time, meal, household chores). In the case of a delay in the departure time to work, more time is available for morning activities, sleep, and pre-sleep activities.

As for the home-bound trip, an earlier departure time provides the traveler with more time for post-work activities at home (mostly spare time, meal, household chores, possibly work). We expect that it would also be associated with work activities during travel to compensate for the lost working time. Earlier travel to work can also be observed, especially if little work is done in the car. In the case of a delay in the home-bound trip, the opposite is expected, with less time available for post-work activities at home, mainly spare time. We expect this would also put pressure on the sleep activity, possibly leading to sleeping later.

Assuming that work activities in the workplace occur between the work-bound and home-bound trip, the change in the duration of stationary work depends on the changes in both departure times.

3 DATA AND RESEARCH METHODS

In this chapter, the research methods, tools, and data required to answer the sub-questions as defined in 1.3 will be introduced, along with their limitations. First, the data source used in this research, which is an existing survey, is described, and its limitations are explored. An introduction of the models to be used follows.

3.1 DATA SOURCES

3.1.1 Data Source Description

In this research, an existing survey/experiment is used as the data source. It was conducted in the period of July 7- July 16 of 2019 in the Netherlands, and distributed online to random respondents. It is targeted towards individuals who travel to work, as those who do not are not allowed to continue the survey. The survey first focuses on the typical travel habits of respondents, such as preferred travel modes and their average travel time on a regular working day. Then, the respondents are asked to provide a representation of their latest working day's schedule, including activities and trips on their preferred mode. The respondents can choose from several options for activities (presented in table 3), and trips to locations corresponding to those activities. In addition to traveling the locations specific to those activities (home, work/school, supermarket, recreation location), other trips are possible, such as picking up kids from school. Figure 4 shows the view of the respondents as they report their schedules by inserting the activities and trip fragments according to the time and duration desired.

Table 3: Activities Available in the Survey

Activities	**Explanation**
Sleeping	Sleeping, taking a nap
Eating	Preparing and eating meals(breakfast, lunch, dinner, or snacks)
Work/ School	Work or education activities
Shopping	Shopping
Household tasks	Cleaning, taking care of children and/or animals
Getting ready	Getting dressed, preparing to go out
Spare time	Leisure, relaxing
Services	Going to the doctor, the barber, the bank etc.
Others	Any other activity (open answer)

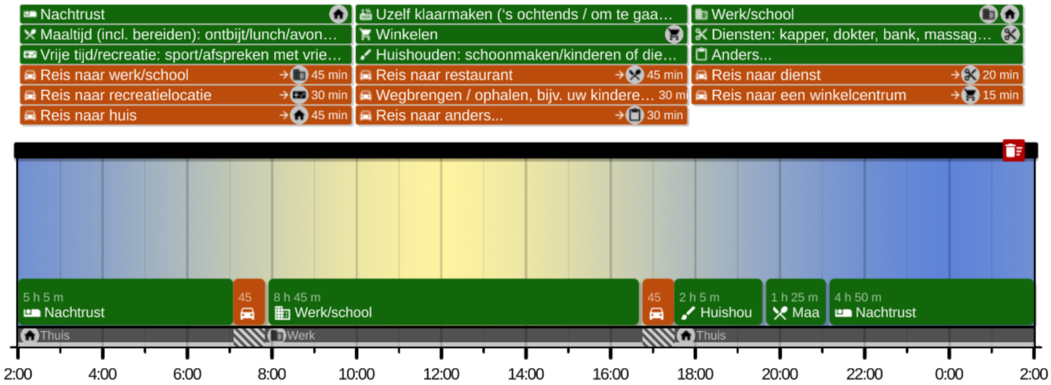

Figure 4: Example of the Schedule Reporting Experiment

After determining their usual daily schedule, respondents are asked to specify their schedule imagining an autonomous vehicle is available to them as a travel mode following the same procedure (see figure 5). The level of activity facilitation on-board (partial or full) is randomly assigned to respondents, thus it operates as a control variable that can be used later to evaluate the influence of motion sickness and activity facilitation. Respondents also have the option to copy the pre-AV schedule and use it as a base for their new schedule, so they do not necessarily have to repeat the process of adding activities and trips. Figure 5 below is a visual representation of the output of this experiment that is available to us to analyze (in addition to data files containing durations, start/end times etc.).

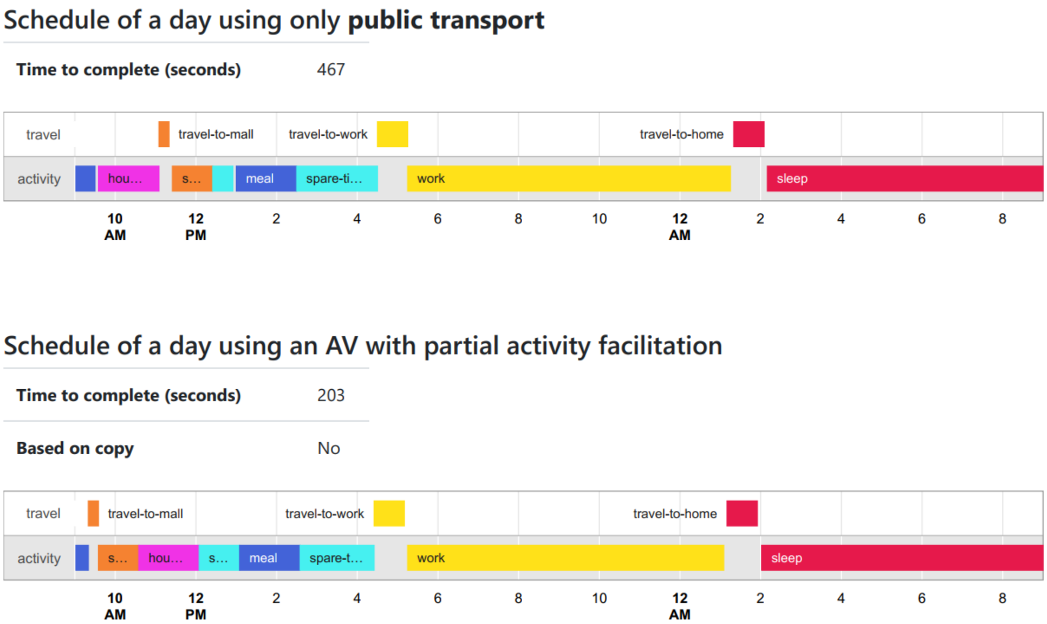

Figure 5: Example of the Survey Schedule Outputs

Finally, the respondents were asked about their perceptions towards cars in general, their knowledge of AVs, as well as their willingness to use one once available to the public. Questions such as "If you had access to an AV, how often would you use it for your daily trips, if the travel costs were comparable with your current travel costs?" aim to provide insights, though limited, on how people perceive the value of AVs in their daily traveling habits. Finally, respondents were asked to provide information about other factors like motion sickness sensitivity, time pressure, and the ability to do work in a vehicle.

While the socio-economic characteristics of the respondents were not directly collected from the survey itself, they are available to us as they have been coupled by the survey platform provider from another database later. With that, the survey content essentially covers five sections : socio-economic attributes , travel characteristics, pre-AV schedules, post-AVs schedules, and AV-related questions. The detailed questions and answer key are presented in Appendix A.

3.1.2 Data Limitations

This research, of course, is constrained by limitations in its data, methods, and general scope. A first limitation concerns the data source. Indeed, considering the survey has already been conducted, there could be limitations related to the data desired. That is, the questions had to be developed and tailored to the data available, there are limits to how far the analysis can go. Nonetheless, the survey is extremely valuable and is sufficient to address the research questions defined.

Furthermore, the constructed schedules may not be fully realistic for several reasons. The first one being that the schedules only represent one day in the life of the respondents, which may not be representative of their general behavior. Additionally, as people experience changes in their lives (new job, new habits...) the schedules they have filled out some time prior may not be valid anymore. Therefore, there is somewhat of a time limit on the accuracy of the schedules. Another limit is that the trips respondents could choose from had fixed travel time range, which puts to question the accuracy of the schedules as complete representations of travelers' daily behavior, and makes the influence of travel time rather difficult to capture. Though this can be addressed by studying and exploring the schedules with the base travel time as a reference. Another limitation is that respondents could only use a single mode of transport in the schedule, the mode they selected as their main one. As a result, multi-modality is not considered in the data, and the influence of autonomous vehicles on such travel behavior can be overstated, and different preferences, like partial utilization of autonomous vehicles, cannot be captured.

Finally, an important limitation of this research concerns the current context in which it is conducted. As autonomous vehicle technology is not available for the public yet, the survey is only based on hypothetical situations that the respondents had to imagine. Therefore, there is a degree of uncertainty that must be considered when analyzing the results, as none of the participants had experienced the technology. Nevertheless, such data still provides insight on individuals' perception of autonomous vehicles, and their readiness to adopt them, which is valuable in understanding how they would react when made available. Thus, the results of this research will be presented within the scope and limitations of the survey. Additionally, underlying assumptions are made concerning which variables are most relevant and should be collected. While the survey designer designed it based on literature and research findings ([64] among others), the survey remains biased towards assumptions from these findings, and thus, is liable to producing biased results and insights. Thus, the results of this research remain to be interpreted within the scope and limits of its underlying assumptions.

3.2 DATA DESCRIPTION

The survey, as described above, represents the activity and travel schedules of individuals, with information on their individual characteristics, from travel preferences to socio-economic traits. With such data, the following questions can be explored and addressed:

- How do individuals change their schedules as a result of autonomous vehicles?
- What variables are most related to each type of rearrangement?

The sample includes working adults and students in the Netherlands. It was administered to commuters, including employed individuals and students who travel to work. To ensure that they are regular commuters, an initial screening was conducted using the first two questions : how often they travel to work, and the length of their commute time. If the respondent answered that he/she travels to work '(Almost) never; I work from home' OR if his/her commute time is less than 10 minutes one way, this person was thrown out of the survey. The goal of this survey is then to compare a regular working day as it is when the respondent uses his/her most frequent travel mode, and as it would be with an autonomous vehicle as the main mode of transport.

Three different data files were produced from the survey, an Excel spreadsheet, a JSON file, and a PDF, each describing the information collected in different forms.

JSON File

A JSON file (JavaScript Object Notation) is a data interchange format, built on attribute–value pairs and array data types. The output JSON file at our disposal provides information in the form of a large list with other embedded lists at multiple levels (4 layers of lists in total). Each response is a single list, with several attributes and their corresponding values. Considering the socio-economic characteristics of the respondents were not collected in the survey itself, the JSON file does not contain this information. As for the schedules themselves, the activities and trips in post-AV schedules were saved in what were called planner. Planner 1 contains pre-AV schedules, while planners 2 and 3 contain post-AV schedules. The distinction between planner 2 and planner 3 is because of the level of automation. As mentioned in (ref here), the level of automation was randomly assigned to respondents, and considering it is assumed that this variable has a considerable influence on the ability to engage in activities on-board, as well as the general comfort levels, the distinction had to be made. As a result, schedules with a partial facilitation level were saved under planner 2, while those with ideal facilitation were saved under planner 3. In the JSON file, the planners are lists, each containing the activity and trips items (also another list), with duration, item type, and start time. As a result of this format, the planner that is does not correspond to the level of automation assigned to the individual does not exist, as the data is essentially dynamically created from the survey and can accommodate disparities in structure size and name.

Excel Spreadsheet

The spreadsheet contains information in the form of columns of variables and rows of responses, with a column containing the individual ID number of each response. The columns contain all the answers of the questions presented in Appendix A, along with the socio-economic characteristics coupled with the data ex-post. In addition, questions about the survey difficulty and improvement suggested are also recorded in columns. Due to the considerable variation in schedules, be it in the number or type of trips and activities, the schedules are not directly transcribed, but rather the individual characteristics of each type of activity and trip is recorded. That is, the number of fragments of each activity type, and the sum of duration of every single fragment are recorded. With this, this data file does not distinguish between the individual fragments, as well as their start and end time. Similarly to the JSON file, there is a distinction between the three planners as introduced beforehand, but it is less structured due to the limitations of spreadsheets, which cannot accommodate variables applying for some responses and not for others. Therefore, the distinction is made through column names, with the activity variables (stationary duration, on-board duration, and fragments) and travel variables (duration and fragments) having the corresponding planner number attached to the variable name. With that, the same variables in the other planner remain, with no values entered.

PDF

The file contains a visual representation of the schedules before and after autonomous vehicles. This is essentially the same view that the respondents had as they were filling out the schedules on the survey. However, the content of this data file is somewhat limited, as it does not provide exact values neither for travel or activity duration, nor for starting times. While a visual comparison of the two schedules is possible, there are considerable limitations, especially when it comes to slight differences, like small changes in departure time. Nonetheless, it remains valuable in initially exploring the data set, as well as cross validating the other two data files.

3.2.1 Data Preparation

Data Cleaning

Though the data has been cleaned, there remain some inconsistencies and illogical responses that must be dealt with. The first step is to ensure that the activities and corresponding trips match and are consistent with the format of the data. That is, we had to scan the data and identify if there were any instances of incompatibility. The ones identified are as follows:

- Incorrect trip type, in which the trip selected does not match the destination. This was dealt with by substituting the entry with the corresponding trip destination in all data files.
- Inconsistent average daily travel duration. Because this was written in by respondents, and there was no accuracy check, some responses were incorrectly entered (70 hours instead of minutes for example). This was dealt with by comparing the entered values with the total travel time from the schedules, cross checking with the entries for daily travel time to work/study, and identifying a more logical value.

The next step is to eliminate responses that are incomplete or illogical. The criteria defined to determine if a response should be eliminated or not are as follows:

- **No sleep activity**. We assume that sleep is a necessary activity that everyone engages in, so any response that does not include sleep is removed.
- **No work activity**. The survey explicitly asks of respondents to provide their latest regular working day, thus, any response that does not include work is considered to be non-compliant and is removed.
- **Conflict in travel activities**. This includes responses with an illogical sequence of travel and activity episodes, such as home-bound trips with no outgoing trips. If the work activities were done at home, there would be no need for a home-bound trip. Thus, we think that such responses are missing outgoing trips, but since we do not have sufficient data to complement that, we choose to remove these responses (3). Another type is an outoging trip with no home-bound trip, which we also believe is non-representative, as a full day is one that begins and ends at home.

While other responses also appear to have issues, as long as they are compliant with the criteria as defined above, they are maintained in the data-set. This includes responses that do not have any travel episodes in the post AV schedule. While this may seem like an error, we assume that this could reflect the individual's reluctance to use an autonomous vehicle.

Data Transformations

With the data cleaned and limited to complete and representative responses, we move on to preparing the data for the analysis. Once the data set imported to the analysis tool (R in our case), variables were converted to their corresponding data class: categorical variables to categorical (Factor), text to characters, and numerical to numerical (some were imported as factors).

While it is impossible to have missing entries in the data, as a respondent cannot submit their response without answering all questions, several optional questions were left unanswered by some respondents, which resulted in some NA values when imported to the data handling and analysis tool. These questions include open ended questions, like "If you had two extra hours per day, what would you use them for?", as well as questions asking for an explanation to a previous answer. The latter follow questions like "Do you suffer from motion sickness during travel?", and ask the respondent to provide details explaining their answer. The final instance of NAs occurs at the level of the planners containing the schedules. While in the JSON file the "empty" planner does not exist, virtue of the embedded nature of its list structure, and thus is not empty per se, the spreadsheet does have empty entries in columns of the planner that does not correspond to the level of automation. These empty columns become NAs when imported. Seeing as these NA values were either not necessary in the case of the optional questions, or a product of an inflexible data format, they are not considered missing values, and are not removed. Instead, they are only replaced by 0s in the case of numeric variables, and by spaces in the case of character variables.

Finally, the average daily travel time was entered as a time variable, but this data is not compatible with the models to be built, so it was converted to a numerical variable, with minutes as the unit.

3.2.2 Descriptive Statistics

After cleaning the data, the final size was N = 493, with mostly categorical variables, with a one numerical variable (average daily travel time). Starting with looking at the distribution of individual socio-economic characteristics in the sample (see appendix B for detailed tables), we observe that the sample is composed of adults, most of them between ages 25 to 54 (73% of the sample). The distribution over the three main age ranges is relatively equal, with the 45-54 range being the most represented at 31%. The sample contains individuals with some level of education,with 50% having at least a university (bachelor, master or doctoral). The remaining are distributed over the remaining education levels, with MBO[1] being the most represented of those at 29%. As for their family situation, 51% of them do not have children, while only 18% are single. The income distribution is quite skewed (figure 6), with 50% of the sample reporting being in the below average income bracket, and 40% in the average income bracket. The remaining 10% falls under the 1-2x the average income range. The distribution of employment is skewed as well, as 73% are salaried employees, while the remaining are either students (9%), government employees (12%) or self-employed (5%). We expect this has implications on the extent to which individuals can do work in the vehicle.

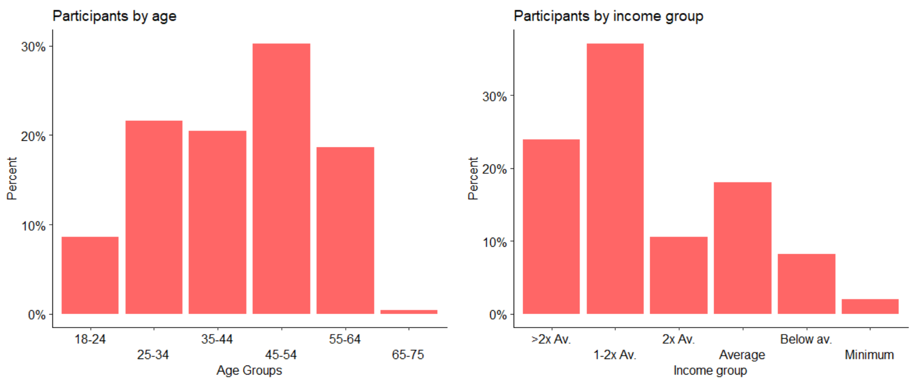

Figure 6: Participants by age and income

As far as the respondents' travel characteristics , we observe that they travel frequently during the week, with 78% of responses reporting travel 4 times a week or more. The remaining travel 1-3 times a week, while no one reports to work from home (note that individuals that did were screened out of the experiment and not allowed to continue). As for their main mode of transport (figure 7)), it is evident that most travelers use the car (65%), while the bicycle (19%) and public transport (15%) account for most of the remaining. What is interesting is that, because 86% of

1 Secondary vocational education

the respondents report to owning a car, not all car owners use their car as their main mode of transport. Few respondents travel long distances during their daily commute, that is for more than 60 minutes (10%), the more common travel times are 10-30 minutes (50%) and 30-60 minutes (40%). As for total average daily travel time, the average is around 79 minutes.

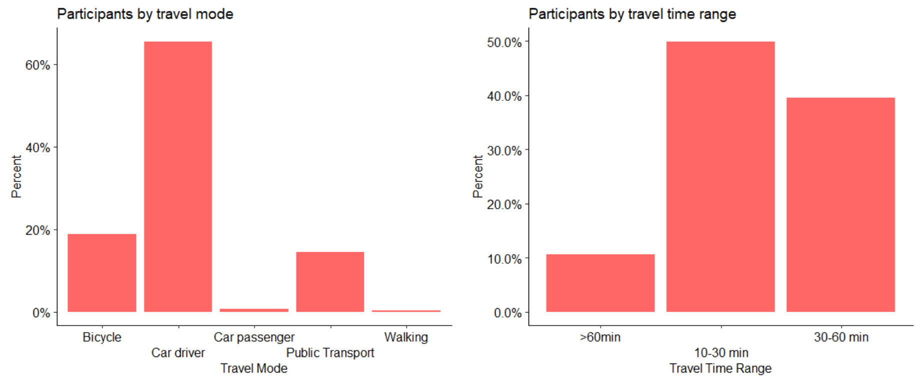

Figure 7: Participants by travel mode and time

Overall, time pressure experienced by respondents is medium to high, as 47% experience medium time pressure and 31% experience high pressure (figure 8). The extremes very high-/very low are less common (3.5% and 2.6% respectively). Motion sickness, however, is scarcely represented, with a total of 19% reporting to have motion sickness always, often or sometimes. The vast majority (81%) hardly experiences it.

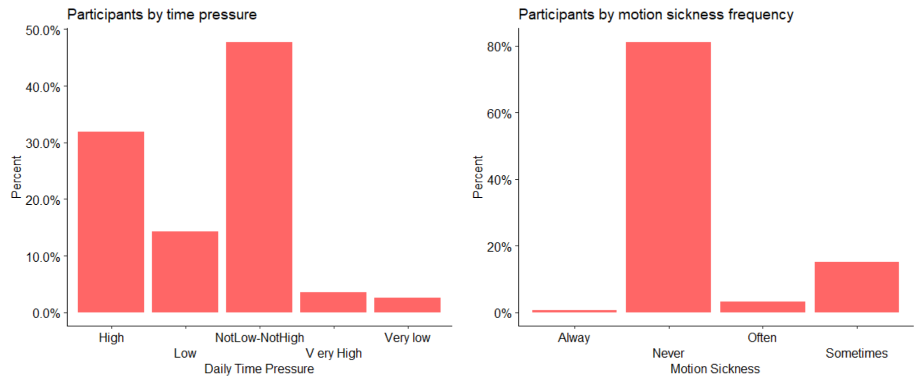

Figure 8: Participants by time pressure and motion sickness experienced

As for the last set of variables, the focus shifts to the expectations of respondents to autonomous vehicles, and how they would expect using one would impact their travel (figure 9). 76% report that they would not change anything to their travel distance, and only 15% expecting they would travel further than they do now. An interesting observation is the uncertainty of respondents in whether they would consider buying an autonomous vehicle, as there is a nearly even distribution over the three main responses (Yes, Maybe, No), with the majority (38%) answering Maybe.

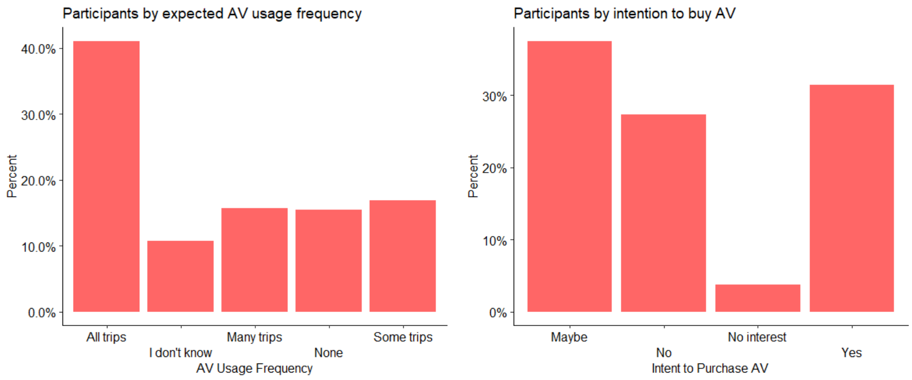

Figure 9: Participants by expected AV usage and intention to purchase an AV

3.3 MODELS

With the data prepared and ready to be analyzed, several analysis and modeling tools can be specified.

3.3.1 Logistic Regression Models

As a first step to studying the indicators that influence the travel and activity choices of travelers, a logistic regression model is selected. Considering the first step is to study the occurrence of changes in schedules, regardless of their type, a proxy binary variable is created to account for the change, which then can be analyzed further using a logistic regression.

Logistic regression models are statistical models that use a logistic function to model a binary dependent variable. The variable has two possible values, 0 or 1, representing pass/fail outcomes. Unlike linear regression models, which predict the value of the dependent variable, a logistic model predicts the logit of the dependent variable using the independent variables. As explained by Peng, Lee, and Ingersoll, the logit is the natural logarithm (ln) of odds of the dependent variable Y, and odds are ratios of probabilities (π) of Y happening to probabilities ($1 - \pi$) of Y not happening [61]. The logit of the dependent variable is then a linear combination of the independent variables, which is represented in the following form:

$$\mathrm{logit}(Y) = \ln(\pi/(1-\pi)) = \alpha + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 ... + \beta_n * X_n$$

α is the intercept, while the βs are the regression coefficients, which describe the effect a unit increase of its corresponding variable has on the logit of Y.The probability of occurrence of the outcome of interest is then:

$$\pi = \frac{\exp^{(}\alpha + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 ... + \beta_n * X_n)}{1 + \exp^{(}\alpha + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 ... + \beta_n * X_n)}$$

The indicators to be selected as the independent variables will be chosen by evaluating several statistical tests and methods, like collinearity, correlations between the variables, and independence. Evaluating model fit with criteria like th BIC, AIC, Rho-squared, p-value and others will be used.

Methodological Design

As we want to explore the occurrence of schedule changes, we choose to do so using a logistic regression in which the dependent variable is the occurrence of a schedule change. We distinguish between three types of changes: on-board activity change, stationary activity change, and travel change. The independent variables to be used to predict these variables will be chosen from the variables available to us (see appendix A for detailed list of variables and key). We distinguish between different types of predictors by their variability, that is how prone they are to be changed in an individual.

- Socio-economic factors: are considered hard indicators due to their relatively stable nature. Indeed, an adult individual's gender, age range, education, and family situation are objective characteristics that do not change easily.
- Travel demographics: are considered softer indicators, though still somewhat robust. Travel time range, travel mode, and frequency are more prone to change than socio-economic factors, but they remain somewhat objective in that they are measurable and observable.
- Personal characteristics: are considered the softest indicators, seeing as they are estimated by the respondents rather than measured or observed. As such, they are more volatile than the other indicators.

These variables are all external to the experiment, as they exist independently.

We do not consider the variables representing the perception of the respondents to autonomous vehicles as predictors. Variables like the expected frequency of usage of autonomous vehicles are largely subjective metrics that we expect are easily influenced by the specifics of this experiment as well as other variables.

Furthermore, the binary variables describing the occurrence of a change (on-board, stationary, or travel) are also not included in the list of predictors, mainly due to the high association between them, which could hinder the identification of the best predictors. Indeed, the correlations between travel change and stationary activity change (0.743), stationary activity and on-board change (0.452), and on-board and travel change (0.279) are all positive and relatively high, which indicates a strong association between them.

Not all variables will be predictors of the change in schedule, so there needs to be a selection of the variables most likely to be good predictors. To reach the final model, a preliminary selection will be made, taking into account expectations from literature, as well as redundancies between variables. A forward step-wise approach in which variables are added by group will be taken, starting with hard socio-economic characteristics, followed by the sequential addition of softer variables.

Starting with the socio-economic individual characteristics, there are several redundancies between variables, that is, multiple variables are descriptors of essentially the same characteristics. This is especially relevant for the family-related variables: family size, family cycle and number of children. Family size describes the number of members in the respondents' family (including themselves), while the number of children describes just that. It is evident here that there could be overlap, as the number of family members directly includes the number of children the person lives with. Family cycle describes the respondent's marital status, age range, as well as age range of children. Not only does this variable overlap with both family size and children, it also somewhat overlaps with age range. This translates into relatively high correlation values between the variables, (0.7677 between family cycle and family size, 0.6611 between family cycle and children, and 0.9207 between family size and children). We choose to exclude family cycle and family size.

As observed in the descriptive statistics section, not all car owners use their car, and while we can expect that car owners would be more open to using autonomous vehicles, the goal of this research is not to predict modal shift to autonomous vehicles, but rather to understand who will be more likely to make use of the features provided by autonomous vehicles. With that in mind, we expect that the preferred mode of transport will be a more descriptive predictor. Indeed, the car owners who do not use their car do so because the alternative mode of transport provides an added benefit, be it speed, comfort, or convenience that is missing in the car. Thus, the mode of transport they actually use provides a better idea of what they are looking for in travel. We choose then to exclude car ownership as an independent variable.

The remaining variables constitute the initial selection of independent variables to be used to build the first model. Next, the model is developed using a backward step-wise approach, in which all remaining variables are considered in the model, followed by a sequential removal of the variables found to be insignificant, all while comparing the AIC of each resulting model. The AIC (Akaike Information Criterion) is one of the metrics used to evaluate the quality of the model. The lower it is, the better the fit.

3.3.2 Latent Class Cluster Models

After identifying the types of changes that could emerge in travelers' schedules, and exploring potential predictors of the binary occurrence of changes, the goal is to better understand how and why those changes would emerge. To do so, latent class cluster analysis and modeling is chosen.

Latent class analysis is a latent variable[2] model that identifies underlying sub-classes in a population, assuming that every individual can belong to one of latent classes. The model estimates two probabilities: the probability of belonging to a class (class membership probability), and the probability of a response conditional to being member of a class (item-response probability) [37]. Many studies, in various fields (social sciences and psychology especially) have used latent class models and analysis to classify individuals into the categories of a (latent) categorical variable on the basis of observed variables [62]. As for the field of transport and mobility, this method is frequently used to in transport studies to predict behavioral changes of traveler classes, often clustered by travel preferences.

We chose to develop a latent class model in this research for several reasons. First, one of the benefits of latent clustering, which is probabilistic as mentioned beforehand, is reducing the biases that come with deterministic clustering methods, thus allowing for more accurate classification [35]. LCA allows us to group respondents by shared attributes that cannot be measured with a single variable, but rather with a combination of variables. Indeed, travelers can be clustered by individual socio-economic characteristics, travel preferences, ability to conduct activities on board and others. Additionally, another benefit of LCA is data reduction, which makes data handling and analysis easier. Indeed, the respondents will be grouped by their most common characteristics, and conclusions can be inferred from the classes rather then looking at each individual response.

The approach we choose to take here is to classify respondents by the chnages they make to their schedules. That is, to consider the transition from schedules before AVs to schedules with AVs, the approach will be to quantify the schedule changes, by computing the differences between the pre and post-AV schedules. The potential variables in question that could be computed are as follows:

- Activity duration
- Number of activities,
- Departure time of trips
- Number of trips

Due to time restrictions and the limited relevance of the fragment changes as will be explored in chapter 4, we will only be able to address activity duration and departure time changes as attributes. As such, the attributes used in the latent class clusters are the duration changes of each activity (working, sleeping, spare-time, eating, getting ready etc.) and the differences between the departure times of several types of trips. Because the sample contains commuters only, our focus will be on the commute trips, that is the work-bound and home-bound trips.

2 A latent variable is one that is not observed or measured

We will try to match types of rearrangements (as identified in 4) with certain trends for the differences in durations. For instance, an observed rearrangement is as follows. The respondent stated that he/she wakes up later, leaves for work later as a result, and begins work in the car. As a result, he/she can leave work at an earlier time and have more free time. This translates to additional activities being conducted, or an increase in an existing activity's duration. The latent class model will allows to identify which class of travelers are more likely to make the specified changes.

Methodological Design

The goal of the latent class clustering is to classify the dataset into the smallest number of latent classes that explain the associations between the different types of rearrangements first, as well as the individual characteristics. These variables are not integrated in the latent class models in the same way, as we make the distinction between effect indicators and covariates. Effect indicators, as per Bollen and Bauldry,can be considered manifestations of the latent variable, while covariates are not measures of the latent variable but are strongly associated to it [7]. With this, the variables measuring the activity duration and departure time changes reflect the global schedule rearrangement experienced by the traveler. Covariates, on the other hand, are exogenous variables like socio-economic factors and other personal characteristics, as they are not measures of the latent variable (the schedule rearrangement), rather they have some influence on it, directly or indirectly. Therefore, base models including the measures of the schedule rearrangements only are made (detailed in 5.2.1), before adding the different individual characteristics as covariates (detailed in 5.2.2).

The process of designing the models begins with fitting a 1-class model (null model), followed by fitting successive models with increasing numbers of classes. There is no commonly accepted single measure of goodness of fit, so different criteria and statistics are used to select the optimal model for the data. One of the most widely used global goodness of fit measures is the Bayesian information criterion (BIC), which allows to compare the fit of the different models. Models with the smallest BIC values are preferred. Another measure to use is the the 'p-value', which provides the p-value for each model under the assumption that the L^2 statistic[3] follows a chi-square distribution [45]. Models with a p-value > 0.05 provide a good fit.

However, it is important to point out that these are global measures, and that in a model with adequate global fit, the fit between two indicators may be inadequate, indicating weakness in the model and possible local dependence. As such, local measures include the bivariate residuals, which assess the extent to which the 2-way association(s) between any pair of indicators are explained by the model [45]. Each BVR corresponds to a Pearson X^2 (divided by the degrees of freedom), and a large value indicates "a potential omitted local dependence"[57]. Magidson and Vermunt determined that a value larger than 1 indicates that the model fails at explaining the association between the two indicators [45]. Thus, we aim to select models with minimal BVR values.

Another criteria we believe to be important in the model selection is the size of clusters. Indeed, while it is not a hard criteria in literature and practice, cluster size can be influenced by outliers and non-representative observations, thus, we set a minimal size limit of 3% of the sample size in order to avoid models with high granulation. Nonetheless, this measure cannot be evaluated independently from others, as a model with acceptable BIC and BVR values may not be rejected on the basis of cluster size. Thus, within reasonable limits ($3 \pm 0.5\%$), models with small clusters can be considered optimal assuming other criteria are adequate.

Additionally, when evaluating the accuracy of models, it is important to consider the magnitude of errors in classification. Indeed, considering this method is built on probabilistic clustering of individuals, there may be errors in class membership assignment. Thus, the proportion of classification, which is generated by the software, will be used as a parameter to evaluate the extent

3 this statistic produced by the software indicates the amount of the association among the variables that remains unexplained after estimating the model

to which the model miss-classifies individuals. The closer to 0 this value is, the better the model is at classifying responses.

3.3.3 Method Limitations

While the latent class model is an effective method to relate the characteristics of travelers with the schedule rearrangements, it does have drawbacks that limit its application scope. One of the first limitations is that it requires a large sample to estimate parameters well [37] [35].

Another limitation the method suffers from is its dependence on the assumption of local independence of indicators. Considering the indicators in this research are individual characteristics of respondents, there may be some dependence that cannot be avoided or measured, which limits the validity of the model. Additionally, latent class analysis can support a limited number of indicator for it to produce representative clusters. Therefore, a selection of independent and influential indicators has to be made, which could then lead to relevant indicators being left out.

Finally, the latent class model provides probabilities of being assigned to a class, so we do not know which class respondents actually belong to, which could make interpretation difficult. Additionally, there could be instances of respondents being assigned to all clusters, or none.

4 CLASSIFICATION OF SCHEDULE REARRANGEMENTS

The first step in our analysis is to identify schedule rearrangements and classify them. Starting with an analysis of the data, we can explore the first research question *What types of rearrangements in travel patterns and activity schedules are expected to emerge with the introduction of autonomous vehicles?*.

4.1 DATA PREPARATION

As mentioned in 3, the survey produced three output files, each containing different data, to be used for different analysis purposes. First, the spreadsheet, as introduced earlier, contains socio-economic variables, travel preferences (mode and frequency), expectations with regards to autonomous vehicle adoption, as well as the schedules pre and post-AV. The schedules are not directly transcribed, but rather the individual characteristics of each type of activity and trip is recorded. As far as the activities are concerned, the following three variables, applied for each activity type, are recorded to represent the distribution of activities in a single schedule:

- Stationary activity duration
- On-board activity duration
- Activity fragments

These three variables describe the number and duration of all nine possible activities both in the autonomous vehicle and out of it, producing a total of 27 variables to represent a single schedule.

As for the travel episodes, they are recorded using different variables. The activity types are also considered here, but the destination is the main distinguishing factor, seeing as some activities can be done in the same location. The eight possible destinations are **work, home, restaurant, mall, service, spare time, drop-off location, other**. The difference here comes from the assumption that there would be no need for individual destinations for household tasks and sleep, as their main location would be home. The variables used to describe the travel episodes in the spreadsheet are similar to those used for activities, with the only difference being that on-board travel duration does not exist, as the trip is by default in the vehicle. As a result, with two variables and eight alternatives, the trip data entries for a single schedule are 16, elevating the total activity-travel entries to 43. Considering the same variables are produced for both schedules, direct comparison between the two is possible, by use of the different planners in which the schedules are saved.

In order to identify the changes in activities, the difference between the post-AV and pre-AV duration of each activity is calculated. This provides an indication to whether the traveler has increased or decreased the total duration of the activity, with the difference in fragments showing if that change has occurred in a single activity block or in many. The duration of the travel activities is available, but because the survey only allowed a fixed travel time, representative analysis of that data is not possible. Nonetheless, the differences in travel fragments can be used to find if travelers have added or subtracted travel episodes from their schedules. Furthermore, the departure times of trips are extracted as well and compared, allowing us to explore potential changes in travel.

As mentioned in the data description section, the level of facilitation (full or partial) of the autonomous vehicle was randomly assigned to the respondent. With this, the AV schedules were saved in the data file as separate variables depending on the level of facilitation. Therefore, we had to merge the variables and differentiate between the level of facilitation through the variable that describes it (task2Type). This distinction has to be made in both the spreadsheet and the JSON file in order to explore the data fully. With this in mind, a analysis of the data starting with the changes in activities, from the emergence of activities on-board to changes in the duration of activities outside the vehicle (mostly using the spreadsheet), followed by an analysis of the various changes in travel behavior, from the number of trips to departure time (using both the spreadsheet and JSON file), ensues.

4.2 CLASSIFICATION OF CHANGES

4.2.1 Types of Activity Changes

It is observed that out of the 493 observations, 219 made a change in the duration of their activities, either in the autonomous vehicle or out of it, accounting for 45% of the respondents. 141 made changes in their on-board activities, 177 in their stationary activities, and 99 in both. First, we start by exploring the entire sample and looking at the differences in duration of activities as mentioned beforehand, shown in table 4 below.

Table 4: Means and Standard Deviations (minutes)of Activity Duration Change (in-vehicle and out-of vehicle), N=493

	In-vehicle		**Out-of-vehicle**	
Activities	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Sleep	0.38	5.33	-2.93	79.50
Getting Ready	0.93	6.024	-0.60	13.14
Work	7.88	25.38	-4.85	42.46
Meal	2.29	9.53	-1.27	25.86
Shopping	0.04	1.57	-0.18	6.08
Service	0.00	0.00	0.98	15.22
Household tasks	0.10	2.22	1.35	17.26
Spare time	7.29	22.70	10.34	73.32
Other	0.34	4.65	-0.67	25.59

The first observation made is the large standard deviation values, especially in the case of stationary activities change. This indicates considerable disparities in duration changes of these activities within the sample. This is mainly observed in activities which experience significant change, like spare time, work, and sleep.

We observe that the activities that experienced the highest increase in duration on-board on average are work and spare time, followed by eating.On the other hand, we observe a decrease in the duration of many stationary activities, work being the most affected, followed by sleep and eating. However, spare time outside the autonomous vehicle does increase, which could indicate that the saved time concept does have an effect on freeing up time outside the vehicle. Overall, the activities most common during travel are **work**, **spare time**, **meals**, and **getting ready**. As for stationary activities, all activities seem to be of interest, but it is important to point out that the means may be biased due to the limited number of instances of changes. Indeed, when looking at the frequencies (see table 5), service, shopping, and others emerge as largely underrepresented variables, as the instances in which a change in the duration of these variables is reported are very few. As such, the weight of the few responses with those changes considerably influence the duration mean, and skew it towards the changes of those few responses. Therefore, taking this into account, the stationary activities of focus will be **sleep**, **getting ready**, **work**, **meals**, and **spare time**.

Table 5: Frequencies of Activity Duration Increase in Decrease by Activity, N=493

	In-vehicle		**Out-of-vehicle**	
Activities	Increase	Decrease	Increase	Decrease
Sleep	8	1	73	38
Getting Ready	21	3	38	45
Work	66	6	47	74
Meal	41	1	37	62
Shopping	2	1	4	1
Service	0	0	2	0
Household tasks	1	0	21	11
Spare time	64	2	88	38
Other	4	1	4	10

An interesting observation is that the sleep activity outside of the vehicle increases more than it decreases, while the mean of the duration is negative. This indicates more people sleep more, but the amount by which they do is lower than the amount by which others sleep less.

One thing to consider with these activity changes is that they are not mutually exclusive. That is, more than one change can be observed in a single response. To identify which possible combinations are most significant, we begin by looking at correlations between the variables. Figure 10 represents visually the correlation within the sample between the differences in duration of each activity. While insight from this figure is valuable, it is important to point out that is represents aggregated information, and some deviations may be observed when looking at individual responses. Nonetheless, these correlations serve as indicators of the level of association between the different activity duration variables, an important step in the exploration of the composition of schedule rearrangements. A positive correlation would indicate that an increase in one variable is associated with an increase in the other, while a negative one would indicate a negative relationship. The colors in the graph below highlight the sign and value of the correlation, blue is the most positive and red is the most negative. The colors are aligned with the size of the circles, which represent the magnitude of the correlation. The largest circle represents a correlation of absolute value 1, a blue largest circle indicates a correlation of value 1, while a red one would indicate a -1 value.

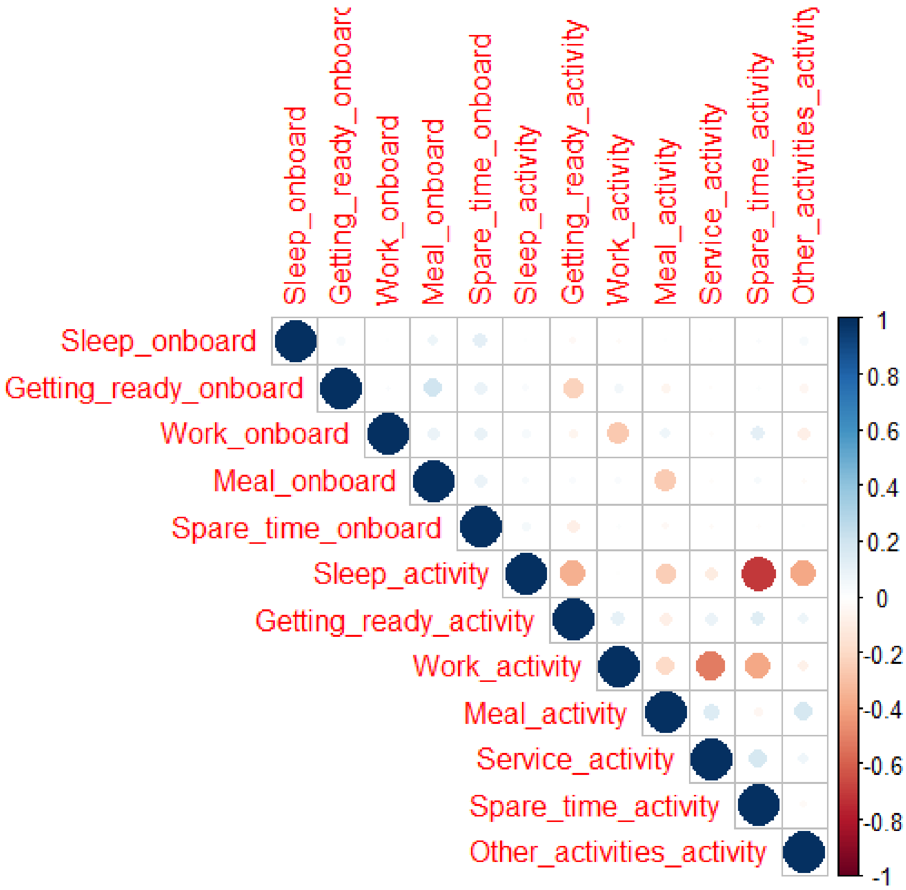

Figure 10: Correlation Plot between on-board and Stationary Activities Duration Changes

It is expected that the increase of an activity on-board would be associated with a decrease in the duration of that same activity out of the vehicle, but this is not observed in all variables. As per figure 10, work (-0.2626), meal (-0.2596), and getting ready (-0.2223) have the highest negative correlations between the stationary activity and on-board. This indicates a possible direct substitution, in which an activity is transferred from a time in the schedule to the travel period.

However, this is not observed for spare time, as the correlation between the stationary and on-board spare time activities is near 0 (-0.016). This indicates that spare time in the vehicle does not substitute for spare time outside of it, especially as it has been observed that stationary spare time duration increases. Thus, the increase in spare time outside of the vehicle is most likely associated with other changes.

What is interesting is that the correlations between the corresponding stationary and on-board activities are not the highest, which indicates that the decision making process is more complex than direct transfer of activities. The highest correlation is a negative correlation (-0.7084) between the stationary sleep and spare time activities. This means that increases in spare time, found to be significant in the data, are often accompanied with decreases in sleeping time (and vice versa, though less significant).

The next highest correlation is also a negative correlation (-0.3873) , this time between stationary work and spare time. Considering the high negative correlation between work in the vehicle and out of it, this could indicate that spare time essentially replaces the original work activity that was moved to the vehicle.

Another high negative correlation is between sleep and getting ready (-0.3527). This can occur when an individual reports they would wake up earlier, thus freeing up some time that can be used to extend the getting ready activity that generally occurs after waking up.

Another high negative correlation is between two stationary activities, sleep and meal (-0.2497). This could indicate that the time freed up from waking up earlier (reducing the duration of sleep) might be used to extend a morning meal activity. In contrast, this could also apply to the evening, in which an extension of the duration of dinner can cause a delay in the bedtime, which can lead to a reduction in duration of sleep if the wake up time is not delayed by enough time.

We note that these are expectations that need to be confirmed by further analysis later, which will control for all interactions and exploratory factors simultaneously. Though the latent class analysis will uncover the combinations of changes in schedules, we can hypothesize on candidate combinations of changes, which could make up the building blocks of possible types of rearrangements. Looking at the frequencies of the most common combinations of changes in stationary and onboard activities (see table 6), we observe that for some activities, there is direct substitution, like work and meals, while it is not the case for spare time.

Table 6: Frequencies of Combinations of Changes in Stationary and Onboard Activities, N=493

		Onboard activities									
		Work		**Spare time**		**Meals**		**Getting ready**		**No activity**	
Stationary Activities		Increase	Decrease	Increase	Decrease	Increase	Decrease	Increase	Decrease		Total
Work	Increase	8	4	5	1	8	0	5	0	27	58
	Decrease	37	1	13	0	9	1	7	2	29	99
Spare time	Increase	30	1	20	0	13	1	7	0	40	112
	Decrease	4	3	3	1	5	0	1	0	27	44
Sleep	Increase	21	2	18	1	21	0	9	0	31	103
	Decrease	7	2	2	1	4	1	3	1	25	46
Getting ready	Increase	9	0	8	0	6	0	3	0	24	50
	Decrease	14	1	11	1	9	1	15	0	19	71
Meals	Increase	8	0	4	0	3	0	0	0	27	42
	Decrease	13	3	15	0	41	0	6	0	24	102
	Total	151	17	99	5	119	4	56	3	273	727

Thus, we find the following combinations to be the most likely building blocks for possible types of rearrangements:

- Work on-board, associated with a reduction in work in the workplace and at home
- Work on-board with an increase in spare time outside the vehicle
- Work on-board with an increase in sleep outside the vehicle
- Meal on-board, associated with a reduction in meals outside,
- Meals on-board with an increase in sleep outside the vehicle
- In the case of no activities on-board, the duration of spare time outside of travel is most likely to increase.

However, these changes do not exist in isolation, as there are also changes to travel behavior, that is in the times of travel and number of trips. This is explored further in section 4.2.2 below.

4.2.2 Classification of Travel Changes

Moving away from activities, we turn our attention to travel. As introduced earlier, different metrics can be used to explore travel changes. While the travel duration cannot be used, as it is constrained by experimental limitations, the number of travel fragments and the departure time can be used. The former indicates the number of trips, and exploring its changes allow us to identify the instances of addition and removal of trips. The latter describes changes in when people expect to travel.

Travel Fragments

As introduced in the data description and preparation sections, the data provided describes the duration of the trips (though it is fixed for travelers), as well as the time of the trips and their number. Starting with the number, presented as fragments, we can evaluate if travelers expect they will travel more or less (see table 7). An initial study of the data shows that 16 respondents have eliminated trips from their schedules, while only 7 have added at least one trip to their schedules. This indicates that there is, in general, reluctance from respondents to make a significant change like adding or eliminating a trip. As for the travel time, 17 respondents report to traveling for longer, while only 8 travel for less time. Considering the limited changes to the number of trips, it is expected that the changes to travel duration are not significant. However, it is important to point that the survey limits the single trip duration to the travel time range they selected at the beginning of the survey. That is, respondents cannot report trips outside that range in either schedules. As such, the changes to travel duration are expected to be limited. Nonetheless, these limited changes can be an indication of the willingness and expectations of travelers to travel more or further. Taking a deeper look to the specific travel fragments, the means and standard deviations of the change in number of trips, shown in table 7, are calculated. In addition, the difference in total travel time is shown as well, though its value is highly dependent on the experimental setting.

Table 7: Means and Standard Deviations of Travel Fragments Change and Total Travel Duration, N=493

Travel Fragments	**Mean**	**Std Dev**
Work Travel	-0.020	0.14
Home Travel	-0.024	0.17
Drop Off Travel	0.004	0.064
Mall Travel	-0.002	0.045
Other Travel	-0.004	0.064
Restaurant Travel	0.0000	0.090
Service Travel	0.004	0.064
Spare Time Travel	-0.006	0.101
Total Travel Duration Change	1.63	13.56

The changes in the number of trips are relatively negligible, which confirms the initial observation that there is little change in how many trips travelers think they will make once they have an autonomous vehicle available to them. As for the travel duration, it is also negligible at less than 2 minutes on average, though the relatively high standard deviation points at a high variation between the responses. While there are limitations set by the experiment, only allowing trips within the travel time range selected by the respondent, the small mean change indicates that changing travel duration is difficult for travelers. Considering all respondents are commuters who have to travel to work or school everyday, some may be obligated to arrive at a specific time, it is reasonable to expect that they would not extend trip duration significantly. There are only 22 reported changes in number of trips, out of 493 observations. When looking at the frequencies of occurrences of changes in travel fragments (shown in table 8 below), we observe that work and home travel are the trips most affected by changes, as these trips are eliminated more often than others. Considering all participants of the survey are commuters, as people who worked from home or were unemployed were not included, commute trips are most likely to be modified, as some respondents only traveled to work and back home.

Table 8: Frequencies of Changes in Travel Fragments by Destination, N=493

Number of Trips Fragments	Addition	Removal
Work Travel	0	10
Home Travel	0	11
Drop Off Travel	2	0
Mall Travel	0	1
Other Travel	0	2
Restaurant Travel	2	2
Service Travel	2	0
Spare Time Travel	1	4

However, we must point out that in 8 of the 22 observations, all trips have been removed in the AV schedule. As mentioned in the data cleaning section of chapter 3, these observations were kept in the data, seeing as they broke none of the rules defined for logic and consistency, as the removal of all trips could be a reluctance to use autonomous vehicles at all. Since this has happened across the data multiple times, we are inclined to believe that it was not a mistake, but rather a conscious decision. On the other hand, some respondents reported to engaging in activities during the time in which a trip was, which indicates that they are interested in autonomous vehicles. A possible explanation is that the respondents may have believed that reporting an activity during the original travel episode was sufficient to communicate that they would engage in an activity during travel, and that they did not need to report the trip itself. For instance, one respondent whose trips were removed in ths AV schedule reported he/she would use an autonomous vehicle for all trips, even explaining that it would be useful for them to do "research or office work" on the go.

Travel Departure Times

While the number of trips and travel duration are found to be limited indicators, partly due to survey limitations as explained earlier, the respondents had more flexibility in terms of the departure time of their trips. Indeed, there were no constraints on the time at which a trip could happen, so we expect there will be more significant changes here.Considering the most common trips are trips to work or to home, we will focus on the changes in departure times of these trips. To do so, the departure times of these trips are extracted from the two schedules, distinguishing between partial and full automation, and the difference is calculated. However, it is to be noted that due to limitations in data handling capacities, we had to assume that a traveler only makes a single trip to work and a single trip home a day. In the case that there is more than one trip of each type, only one is included in our analysis. In order to avoid biased analysis with inconsistent differentials, the responses which have at least more than one work/home trip in either schedules or both (pre- and post- AV) are studied separately. The total of these observations is 73 observations, or 15% of observations.

The remaining data, consisting of 420 observations, can be looked at further without the possible noise of the other observations, which will be explored individually later. Looking at the means and standard deviations (see table 9, we observe that the largest change occurs for home travel,of which the departure time seems to decrease. That is, many travelers report that their trip home would happen at an earlier time once they have an autonomous vehicle available to them. The decrease for the work trip appears to be less dramatic, which could indicate that the delays in the departure time for that kind of trip are frequent as well.

Table 9: Means and Standard Deviations (minutes) of Changes in Travel Departure Time by Destination, N=420

Travel Time Change	**Mean**	**Std Dev**
Work Travel	1.19	16.10
Home Travel	-7.38	77.45

It is observed that the standard deviation of home-bound travel time departure change is considerably high, indicating a significant variation within the sample. However, when looking at the frequencies (See table 10), it appears that the most common form of change to travel times is traveling to work later. This indicates that home-bound travel is advanced more significantly than work-bound travel is delayed, though the latter occurs more often in schedules.

While it is possible that each change occurs independently, we can explore the frequency of the possible combinations (see table 10. We observe that the most common combination (besides no change) is a delayed departure time to work with no change in the departure time to home. Another common combination is an earlier departure time to work and no change in the departure time of the homebound trip. When there is a change in the departure time of the homebound trip, it is generally earlier, with earlier and later trips to work being equally common.

Table 10: Crosstable of Frequency of Changes in Travel Time by Destination, N=420

		Time of Trip to Home			Total
		Earlier	Later	No change	
Time of Trip to Work	Earlier	18	9	2	29
	Later	25	17	12	54
	No change	19	6	312	337
Total		62	32	326	420

Going back to the responses removed due to the high number of trips (N=73), we delve deeper into the different combinations in those cases.A crucial distinction to be made here is the change in number of trips. Here, we focus on responses with multiple trips and no change in the number of trips, as that is the only way we can compare changes in departure times. Indeed, when a trip is removed, direct comparison is not possible, so they are explored independently below. First, we must consider the responses in which all trips were removed, which amount to eight. In these, since we cannot know for certain the reason for this change, we assume that no change has been made in the number of trips and their departure time. As for the responses with removed home-bound and work-bound, they are only three, and comparison was possible for all three. Indeed, the consequences of eliminating a trip or more were not dramatic, and the remaining trips were only slightly delayed or advanced, so there were little doubts over which trip it corresponded to. As such, we can include these responses in table 11. In all three trips, the work trip, or trips, were advanced, while the home trip was delayed. In the case of multiple trips with no change in the number of trips, we observe that changes in departure times are few. Starting with responses with two home-bound trips and a single work trip, the majority (54 out of 73) do not report any changes in departure times of any of the trips. When there is a reported change, all trips are changed, with an earlier departure time being most common. Overall, as shown in table 11, the most common change in departure time is moving the trips earlier, both home-bound and work-bound. It is noticeable, however, that no change remains most common.

Table 11: Crosstable of Frequency of Changes in Travel Departure Time by Destination, multiple trips, N=73

		Time of Trip to Home			Total
		Earlier	Later	No change	
Time of Trip to Work	Earlier	4	3	1	8
	Later	2	1	0	3
	No change	5	3	54	49
Total		11	7	55	73

Thus, we conclude that the most significant change in travel occurs at the level of departure times rather than the number of trips. Thus, we expect that the following types of travel related changes are most common in the data, and can be used to classify responses:

- No change in travel departure time
- Earlier departure time to home
- Delayed departure time to work

5 FACTORS ASSOCIATED WITH SCHEDULE REARRANGEMENTS

With the rearrangements in schedules identified, the next step is to explore the factors associated with these changes, in order to better understand the circumstances under which these schedule changes may emerge. Thus, we aim to study the second research question *What factors and characteristics of travelers are associated with the specific activity schedule rearrangements?* starting with logistic regression models (5.1), followed by latent class cluster models(5.2).

5.1 LOGISTIC REGRESSION

As seen in chapter 4, on-board activities and changes in stationary activities often occur simultaneously, and while it is likely that the possibility of engaging in on-board activities drives the changes in other activities, there remains possibilities of the opposite being true. It is difficult to pinpoint which of the decisions happens first, or in which direction the effect is, so we assume that it goes both ways. On-board changes can lead to changes in other activities, but activities can be intentionally modified to accommodate for on-board activities. The effect on travel changes is slightly more straightforward, as we assume the activity changes to directly impact travel, as changes in activity duration move the next travel departure time. Considering there is a strong association between on-board changes and activity changes, considering the effect of on-board changes on travel changes would be redundant, so we consider that most of it would be through activity changes.

The responses that we aim to predict with regression models are binary variables describing changes in schedules. We distinguish between changes in on-board activities, in stationary activities (duration, number of activities, and change in order), and travel (departure time, number of trips). Binary variables were created to describe if each of these changes have occurred (more details of the specific changes are found in chapter 4). As shown in figure 11, most of the changes that do emerge relate to the stationary activities, with 36% of responses reporting to making some change in the duration, number, or order of their activities. As discussed in chapter 4, not all of these changes are prompted by on-board activities, as can be concluded from the disparity in proportion of responses that report changes in each category. 29% report to making changes to their activities on-board, while only 25% have made changes to their travel.

	Data (N = 495)
On-board Activity Addition	
Yes	142 (29)
No	353 (71)
Stationary Acitivity Change	
Yes	179 (36)
No	316 (64)
Travel Change	
Yes	125 (25)
No	370 (75)

Figure 11: Frequencies of the Response Variables

This section will explore and identify the factors that influence the decision to make a change in the schedule. As such the dependent variables to be used will be three binary variables which reflect if changes have been made at each of the identified levels: stationary activities, on-board activities, and travel changes. Logistic regression models will be developed to estimate the influence of several variables, with the goal of identifying "who" makes changes in their schedules.

5.1.1 Model Results

Base models with the set of variables identified in the previous section are built, with the aim of predicting the occurrence of activities during travel, a change in the activities outside of travel, and travel itself. The final models designed following the step-wise approach defined earlier are found in appendix C. As mentioned earlier, the step-wise model development approach begins with hard socio-economic factors, with the aim of identifying the extent to which schedule changes are driven by the stable characteristics individuals themselves. With this, we find that the influence is minimal at best, with only on-board activities being somewhat influenced by gender, education, and income. Interestingly, age was found to have little predictive power on any of the three schedule change indicators. Starting with gender, we find that men are less likely to use the traveling time for activities. While we can speculate this would be due to women's inclination to multitask, the influence of gender may be overstated here as women constitute 37% of the sample. As for education, travelers with higher education levels seem to be more likely to engage in activities during the travel time. It is possible that this could be an experimental artifact, as highly educated individuals would find filling the survey easier. However, the correlation between the education variable and the survey difficulty variable is very low, and of the respondents with at least a university degree, only 8% of them found the survey difficult. Thus, we can assume that the significant influence of education is not a result of the experimental setting.
Income was found as a significant predictor of travel change and on-board changes, but its influence was not as we expected. Indeed, higher income negatively impacted the probability of making travel changes. That is, higher income individuals were still less likely to make travel changes in comparison individuals earning minimum income. However, considering only 10 out of the 493 observations studied earn minimum income, we cannot conclude that lower income individuals are more likely to make travel changes. However, as we compare the other income ranges, we see that the negative effect is lower for higher income. As such, income may actually be associated with more travel changes.

Travel characteristics, which were considered softer indicators than socio-economic factors, played a more significant role in predicting the schedule changes on all three levels. The most significant variable identified was travel time, with travel mode and frequency being less relevant. As introduced earlier, it was expected that longer travel time provided more opportunities and flexibility for travelers to engage in activities, possibly more than one in a single trip. This was confirmed by the regression model, finding that travel respondents whose travel time was between 30 to 60 minutes were 0.66 times more likely than travelers with travel time less than 30 minutes to engage in activities during travel. As for stationary activities, the effect was less evident initially, but the models showed that travelers with longer travel time were found to be more likely to experience change in their stationary activities. This influence could be an indirect result of the reinforcing effect of long travel time on the occurrence of activities during travel. As such, a possible path for on-board activities is transferring existing activities happening outside travel times to travel periods, freeing up time and triggering further schedule changes affecting the duration or number of stationary activities. In the case of travel changes, only travel frequency proved to significantly predict them, with, interestingly, individuals traveling less frequently (1-3 times a week as opposed to 4-5 times a week) were more likely to make changes to their travel, be it departure time or number of trips.

Finally, of the remaining personal characteristics work flexibility was found to be the most significant predictors. The model confirms the expectation that when less work tasks are possible in the car, the traveler is less likely to engage in activities on-board. A similar effect is found with respect to stationary activities and travel changes, but was only significant for the former. Interestingly, the magnitude of the negative effect of the most extreme response no task is possible in the car is much larger on stationary activity change than on on-board activity change. However, as we consider other "soft" variables, we find that they have little influence on any of the schedule change indicators. Daily time pressure, which we anticipated would be a significant driver of on-board changes, especially as it would include the effects of both personal and professional responsibilities on time use, was found to be largely insignificant. Furthermore, while we expected motion sickness to limit multitasking during travel, the effect observed was hardly significant, though it matched the expectations, as individuals who experienced motion sickness less regularly were more likely to make changes on-board. Activity facilitation also served no purpose in enhancing or diluting this effect. As such, we can estimate that, based on these insights, that discomfort on-board was not a significant obstacle for multitasking during travel for the respondents of the survey. It is to be noted, though, that the proportion of respondents who almost never experience motion sickness is 80% of the sample, so these insights may not be representative of the population.

5.1.2 Conclusions

With the results of the models in mind, we have identified the significant causal relationships between individual characteristics and attributes and the occurrence of activity-travel changes, and adjusted the conceptual model developed earlier, see figure 12.

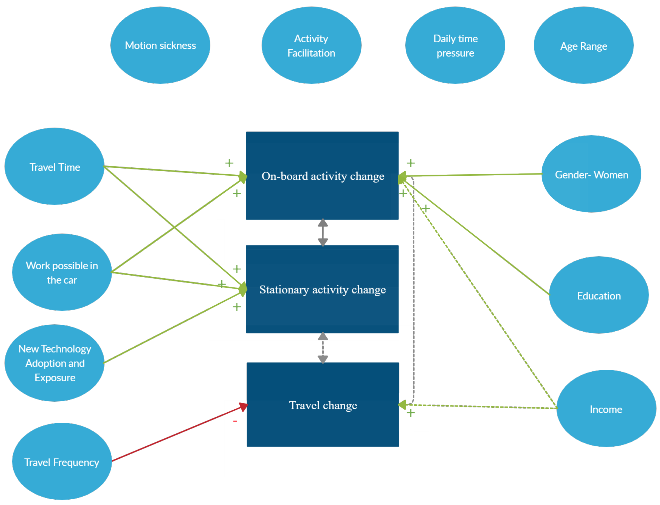

Figure 12: Summary of Significant Causal Relationships between Indicators and Schedule Changes

To summarize, we have identified that individual and travel attributes influence different elements of schedules in various degrees. Starting with on-board activities, socio-economic factors have a significant influence on the occurrence of activities during travel. Women and highly educated individuals were more likely to engage in some activity during travel, while the influence of income was more complex, mostly due to the low representation of the reference income (range minimum income). Based on our interpretation, we find that higher income individuals would be more likely to multi-task, but this effect is most significant for the highest level of income. That is, most individuals who earn up to twice the average income would multitask during travel, while individuals who earn more or less the average income would have a more varied response. This could be in parts due to the high representation of average income individuals (38% of the sample), which entails more variety in the expected changes. Travel characteristics' influence is mostly through travel time, as the expected association between longer travel times and activities during travel is confirmed. Interestingly, travel mode was not significant in predicting these changes, and though it may be due to the over-representation of vehicle drivers in the sample (car drivers constitute 65% of the sample), it remains clear that the current preferred mode of transport did not guide the choice to engage in activities on-board in the same way across the sample. A significant influencing factor is the ability to do work during travel, which confirms our initial hypothesis. Evidently, travelers who are able to do more work tasks during travel would be more likely to do so, but we find that the negative influence of the most extreme response (no task possible in the car) is the most significant. This highlights that the levels of remote work flexibility are similar in how they influence the binary occurrence of activities on-board, but the difference would be more apparent when looking at durations of each activity type on-board. Finally, the other "obstacle" factors that we hypothesized would influence the decision to engage in activities on-board (daily time pressure, motion sickness and activity facilitation level) were found to have little to no significant influence.

Moving on to the stationary activity changes, we find that none of the socio-economic attributes can be considered significant predictors. That is, the occurrence of changes to stationary activities, regardless of the kind of change, has little to do with the characteristics of the individuals themselves. While this could be interpreted as the stationary changes not stemming from the individuals themselves, but rather from other schedule changes that trickled down to these activities, we acknowledge that the logistic regression models do not capture the variety in activity types. As such, associations between these attributes and specific activities (work, spare-time, meals etc.) may be stronger. Similarly to on-board activities, travel time is the most significant predictor out of the travel characteristics variables. A similar effect is observed, with longer travel times often being associated with stationary activity changes. While we did not expect the ability to do work in the car to influence stationary activity change, we identify a significant effect, similar to what was observed with on-board activities. As mentioned earlier, the individuals who could not do any work task in the car were almost completely unlikely to make a stationary activity. Because this variable mainly concerns the ability to do an activity on-board, we speculate that this effect, much larger than the one on activities on-board, may be a result of the combination of the direct influence of this variable, but also the indirect influence through on-board activity change.

Finally, in the case of the occurrence of travel changes, we find that income significantly influences the decision to make travel changes. The effect itself is similar to what was observed with on-board activities, with higher income individuals being less likely to make travel changes in comparison to individuals earning the minimum income, though with any other reference, the opposite is true. Aside from income, no other socio-economic factor is significant in predicting the occurrence of travel changes. As for travel characteristics, travel frequency emerges as a significant predictor, highlighting a negative association between the number of trips one takes a week and the likelihood to make some change to said trips. Indeed, frequent travelers are less likely to modify their travels, which we speculate could be due to more stringent work rules, as we think that commuters who do no travel everyday would have more flexibility in terms expected arrival time to the workplace than those who travel everyday. Finally, none of the remaining personal attributes were found to significantly influence the decision to make travel changes. Though this was expected in the case of some variables (motion sickness, ability to do work in the car), others like daily time pressure were surprisingly not significant. The effect of daily time pressure is as expected, as the higher the time pressure the more likely a travel change would occur, but the overall effect was still negative with respect to the lowest level of time pressure. Nonetheless, as this effect is not significant, we cannot make inferences of the impact of daily time pressure on the occurrence of travel changes.

As instructive as these insights have been, they do not cover the full extent of the factors influencing the different types of schedule rearrangements. Indeed, we find that few indicators significantly predicted the occurrence of activity and travel changes, but we believe that the limitation of only binary changes, encompassing all possible types of arrangements, largely "hid" many of the possible associations. We believe that some attributes that were found to have little influence may be more significantly associated with specific types of changes. As such, there is a need for a wider exploration, directed towards the different kinds of possible changes including all activity types (work, spare-time, meals etc.) and travel changes ()trip departure times). More specific questions like "What factors lead to an increase in spare-time outside travel?" should be addressed. Furthermore, the limited coverage of the logistic regression models (the highest Pseudo R-squared was 11%) highlighted the significance of the interactions between the different components of activity-travel schedules (on-board, stationary activities, and travel). That is, several single changes may be resulting from other single changes e.g an individual spends more time relaxing after work because they traveled home earlier (the causal direction is arguable). In this, the logistic regression fails to capture such interactions.

With the insights from the logistic regression models in mind, along with their limitations and shortcomings, we acknowledge the need for further exploration of the possible, and common, combinations of single rearrangements, in association with the individual attributes of the respondents. Therefore, another approach considering the full variation of possible changes, not only the binary occurrence of a change in schedule or not, is needed. Latent class cluster analysis provides a method to identify factors associated with schedule rearrangements, in all their different types and combinations, through classifying the respondents into homogeneous clusters based on the reported changes they have made to their schedules, as well as their individual characteristics and attributes.

5.2 LATENT CLASS CLUSTERING ANALYSIS

Though the logistic regression models provided some insight into the influence of personal and travel characteristics on the occurrence of schedule rearrangements, this approach is limited in that it only considers binary changes and does not consider the variations in the specific rearrangements. A whole schedule rearrangement is composed of smaller single rearrangements in activity duration, during travel and outside, as well as in the trips themselves. Not only can these changes occur as single changes, they can also bring about other changes. Since the logistic regression cannot capture these interactions, latent class cluster models will be used to explore and better understand the specific schedule rearrangements in relation to the individual characteristics of the respondents, but also considering the interactions and influence of single changes. Latent class cluster analysis will be used here to distinguish between heterogeneous classes of respondents in the data by the schedule changes they have reported, as well as by their personal characteristics. As introduced in Chapter 3, latent class clustering is a model-based clustering method that deriving a useful division into a number of classes, where both the number of classes and the properties of the classes are to be determined.

5.2.1 Clustering by Schedule Changes Only

Starting with the change indicators only, that is the activity duration and departure time changes, the goal is to identify classes of respondents with similar changes. This serves to confirm the prevalence of certain changes over others, initially identified through the first exploration and classification in chapter 4, and explore combinations of rearrangements. Based on the findings of the data exploration conducted in chapter 4, the duration change variables were the most significant, as were the travel departure time change. Therefore, we choose these variables as indicators, with focus on the activities that experienced the most significant variations. As such, we choose to build our clustering models with the indicators shown in Table 12:

Table 12: Activity and Travel Change Indicators

On-board Activity Duration Change	**Stationary Activity Duration Change**	**Travel Departure Time Change**
Work activity	Work activity	Home-bound trip
Spare time activity	Spare time activity	Work-bound trip
Meal activity	Meal activity	
Getting ready activity	Getting ready activity	
	Sleep activity	

While it is possible to use the duration changes of these activities, an important factor to consider is the the influence of the travel time. Indeed, as introduced in the data limitations section (see chapter 3), the respondents could only report trips of duration within the limits of the single trip travel time range they had selected earlier in the survey. As such, the effect of autonomous vehicles on travel duration is understated and cannot be completely explored. In addition, it introduces a bias in the activity duration changes, as travelers with longer commute travel time have more flexibility for introducing on-board activities, while travelers with shorter commute travel time, who may be interested in traveling longer in order to be able to engage in more activities, are severely limited by this experimental artefact. While it is possible to travel more to increase the travel time, chapter 4 has shown that the changes in travel fragments, as in the number of trips, is negligible at best, with removal of trips being more commonly observed as opposed to addition of trips. As a result, there is a significant bias in the changes to be observed resulting from this limitation, not only in on-board activities, but also in stationary activities, as there is a strong association between the two. Indirectly, the departure times are also limited by this, as changes that could have been brought about by longer travel (respondents who may want to travel longer may also want to travel earlier) are not captured. In order to address this limitation, we choose to use not absolute duration differences, but rather proportions of the duration change to the total travel time. We choose to use the sum of the trips of each individual in the pre-AV schedule as opposed to the travel time range respondents provided (which divide them into 3 main groups). The resulting numbers essentially describe the relative activity duration change, as well the departure time change, relatively to the total travel time.

On-board and Stationary Activity Duration Change Model
Before building models with all duration change indicators, we begin with individual models with on-board duration changes and stationary duration changes separately (see more detailed analysis in Appendix D). Starting with on-board activities, the differences between the clusters are clear, as seen in figure **??**. Aside from the cluster of no-change (cluster 1), the next largest clusters are ones in which a single activity is dominant. As such, a work-focused cluster (cluster 2) and a spare-time focused cluster (cluster 3) emerge, highlighting a group of travelers for whom the value of autonomous vehicles is tied to the ability to engage in those activities. The final cluster, however, introduces a new group, which makes use of the travel time differently, choosing to engage in different activities in almost equal proportions.

Figure 13: Summary of the Cluster Profiles with On-board Duration Change Indicators only

As for stationary activities, a no-change cluster emerges as the largest grouping, but other interesting changes exist (see figure 14). Cluster 2 represents the group of travelers who spend less time working, and more time on leisure and spare time. We can hypothesize this arrangement could be the result of transferring some work tasks to travel episodes. The remaining two clusters show similar patterns of changes, with decreases in meal time and work tasks and increase in sleep. Nonetheless, a general tendency to spend more time getting ready and less time working and eating is the main distinction between the two.

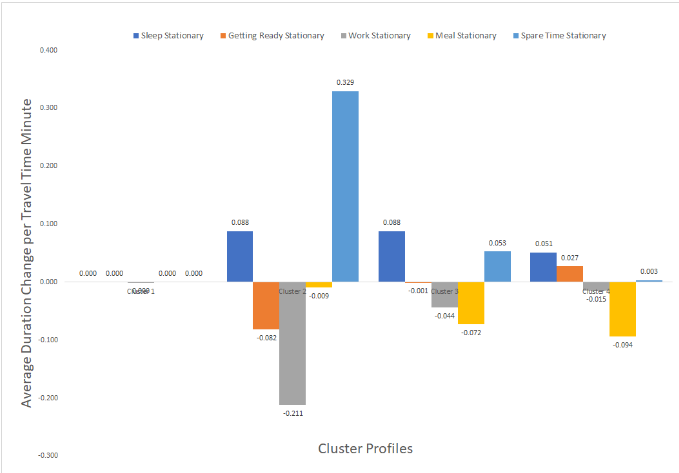

Figure 14: Summary of the Cluster Profiles with Stationary Duration Change Indicators only

Evidently, the value of these insights is limited when the interactions between the two types of changes are not considered. Indeed, our initial exploration of the data highlighted the existence of a strong association between the occurrence of on-board activity changes and stationary activity changes, indicating that individual time allocation choices are linked. The next step is then to identify the combination of stationary and on-board activity changes. We begin with a model including all activity duration change indicators, on-board and stationary. Using the evaluation criteria introduced in 3.3.2, a 5 cluster optimal model is identified, as shown in Table ??.

Table 13: Latent Class Profiles of the 5-class Solution with Stationary and On-board Activity Duration Change Indicator

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Indicators- Duration Change	Cluster Size (%)	55.91%	15.13%	10.38%	10.05%	8.53%
Getting Ready On-board	Mean	0.000	0.000	0.105	0.000	0.000
Work On-board	Mean	0.000	0.000	0.185	0.175	0.485
Meal On-board	Mean	0.000	0.000	0.124	0.000	0.146
Spare Time On-board	Mean	0.000	0.000	0.278	0.490	0.001
Sleep Stationary	Mean	0.000	0.042	0.072	-0.002	0.152
Getting Ready Stationary	Mean	0.000	0.025	-0.109	0.000	0.005
Work Stationary	Mean	0.000	0.066	-0.141	0.008	-0.339
Meal Stationary	Mean	0.000	-0.013	-0.114	0.000	-0.073
Spare Time Stationary	Mean	0.000	0.030	0.220	0.009	0.218

Again, the majority of respondents (55.91% of the sample) fall under the no-change cluster. Indeed, members of cluster 1 believe they will experience little change in their activity schedule, be it during the travel episodes or outside of travel. It must be pointed out that we are not using absolute duration difference, but rather proportions of these differences and the total travel time, so small changes will be minimized. Similarly, cluster 2 (15.13% of the sample) reflects little changes in the duration of activities on-board, with mostly a slight increase in work and sleep outside travel. Because the no-change cluster in the on-board change model is larger than the no-change cluster in the stationary change model, this cluster emerged as a result of the addition of indicators.

Cluster 3 (10.33% of the sample) is the multi-activity cluster identified in the earlier model, with its members engaging in all activities on-board, especially work and spare time. Because work, getting ready, and meals duration outside travel generally decreased, we expect that many of these activities would be transferred to the travel episodes. Comparatively, stationary spare time increased, although it is significantly present on-board. This indicates a high need and demand for leisure that could not be satisfied within the available time, so the additional useful travel time provided an option for additional relaxing. Furthermore, the variety in on-board activities indicates that travelers may engage in more than one activity per trip, and that they may not engage in the same activity in both the work bound and home bound trip. The latter possibility is confirmed in literature, as travelers are likely to use the home bound trip to "switch-off" and relax [82].

The next two clusters are single activity focused, as members of cluster 4 (10.05% of the sample) engage in mostly spare time activities during travel, with some work as well. Interestingly, despite this increase in work tasks on-board, there is a slight increase in stationary work activities, which could hint at possible work from home. Similarly, the increase of spare time duration on-board is associated with an increase, though quite small, in spare-time duration outside travel, indication addition of spare time activities beyond the existing ones in the original schedule. The higher increase in spare time on-board, associated with little change in stationary activities shows that these travelers could want to use the autonomous vehicle for enjoyment and leisure rather than for functional purposes. This could indicate that they experience high pressure and stress during travel, and that they would benefit from being relieved of the driving responsibility and the expected additional comfort provided in an autonomous vehicle.

The final cluster (8.53% of the sample) is a work-focused class, in which travelers mostly engage in work activities during travel, and to a lesser extent, meals. Both are reduced outside travel, indicating transfer, though not complete, of activities. With more time available outside travel, other activities like spare-time and sleep are increased. We can then assume that the activity transfer to the travel episodes served to free up time for other activities, with possibly the purpose of reducing time pressure associated with work.

Overall, combining both activity duration change indicators shows that the same patterns observed with on-board activities remain (no-change, single activity increase with spare-time or work, multi-activity increase), while insights on the associated stationary activity changes emerge. Direct activity transfer is more common with work, meals, and getting ready, indicating that there is no additional demand for these activities beyond the original schedule, while the need for spare-time seems to be higher than could be satisfied in the original schedule. As such, the addition of the travel time as "useful" time provides an opportunity to satisfy that demand.

Travel Departure time, On-board and Stationary Activity Duration Change Model
Finally, in order to get the complete picture, including the possible interactions between all indicators, a 5-cluster model with the three types of changes is made, as shown in the cluster profiles in Table 14 below. The addition of departure time changes had some influence on cluster profiles, though the main classes as identified earlier remain, but also a significant influence on cluster sizes. Indeed, the 3 main types of on-board activity focus (no-change, single activity increase with spare-time or work, multi-activity increase) remain, but the no-change cluster became smaller with the addition of two new variables. A larger work only on-board cluster emerged, as did another multi-activity on-board cluster.

Table 14: Latent Class Profiles of the 4-class Solution with On-board and Stationary Activity Duration and Departure Time Change Indicators

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Indicators	Cluster Size (%)	44.22%	18.38%	18.17%	10.63%	8.60%
Getting Ready On-board	Mean	0.000	0.000	0.000	0.079	0.030
Work On-board	Mean	0.000	0.186	0.000	0.192	0.281
Meal On-board	Mean	0.000	0.000	0.000	0.131	0.135
Spare Time On-board	Mean	0.000	0.000	0.243	0.231	0.090
Sleep Stationary	Mean	0.000	0.054	-0.001	0.140	0.019
Getting Ready Stationary	Mean	0.000	0.033	0.000	-0.082	-0.038
Work Stationary	Mean	0.000	-0.047	0.000	-0.059	-0.219
Meal Stationary	Mean	0.000	0.005	-0.001	-0.102	-0.115
Spare Time Stationary	Mean	0.000	0.101	0.007	0.113	0.176
Work Trip Departure	Mean	0.000	0.001	0.059	0.002	0.024
Home Trip Departure	Mean	0.001	0.000	-0.125	0.000	-0.061

Again, the no-change cluster is the largest one, with 44% of the sample. Considering the change indicators were used as proportions, the small variations were minimized further, so no changes at all are observed. Essentially, this is the group of travelers who expect that their schedules would not experience any modifications at all. This may be due to multiple reasons, low time pressure so there is no need to transfer activities to the travel episode, or lack of exposure to technology, so they do not know/trust it, or they cannot transfer activities to travel, like work tasks. or their travel time is too short to be able to do anything. All of these can be explored by including the personal characteristics and socio-economic factors as covariates, which will be done in the next section.

The single activity clusters remain important, with cluster 2 (18.4% of the sample) including travelers who mostly benefit from the additional time during travel to do work, with the goal of freeing up time outside travel. Indeed, the duration of work outside travel is reduced in this cluster, while spare time increases, indicating that there was a need for more leisure that could only be satisfied once the travel time became available. Considering they sleep longer and spend more time getting ready, we expect that they travel slightly later in the morning and work in the car. The changes in travel departure time are minimal, though the small delay shows that some travelers in this group do travel to work later, indicating that they have more time in the morning to eat and get ready, but also that they may also wake up later in the morning. Cluster 3 (18.2% of the sample) is similar in a single activity, spare-time in this case, is most common on-board. Similarly to what was observed earlier when travelers engage in spare-time on-board, the duration of spare-time outside travel increases. Patterns of departure time change appear as well, as this group of travelers tend to travel home earlier and leave to work later. Returning home earlier allows more time for post-work activities, namely spare time and household chores.

As for the multi-activity on-board clusters, the addition of the departure time change indicators has led to the emergence of a new cluster (Cluster 5, 8.6% of the sample) in which travelers engage in all activities on-board, with work being the most prominent. As such, the time spent eating, working, and getting ready outside travel is decreased, as some activities may be transferred to the travel episodes, while sleep duration increases. Spare time, though its duration on-board increases, also increases outside travel. This is partly due to the earlier travel home, which frees up time for after work activities, generally spare time and household chores. With this, it is also probable that travelers in this cluster sleep earlier. Considering the time they spend getting ready and eating also decreases while they tend to travel to work later, we expect that many of them would wake up later. Cluster 4 (10.6% of the sample) represents essentially the same group of travelers as cluster 3 from the previous model (see table 13, who engage in all activities, spare-time slightly more so than others. As expected, activity transfer is observed for work, getting ready, and meals, but not for spare-time, as it is the only activity to increase both during and outside travel. The travel departure changes are not very larger, but the slight delay in work-bound trips indicates that this group of travelers may delay their wake up time, as the duration of sleep is increase, and tasks that would generally be done in the morning, such as eating breakfast and getting ready, seem to be transferred to the morning trip. While there seems to be no change in the home bound trips' departure time, the most likely change would be an advancement of these trips, but it is likely to be too small to be significant in comparison to the morning trip delays.

Overall, the inclusion of the departure time changes adds another dimension of interaction to the schedule changes. Indeed, we observe that delays of work-bound trips are often associated with decreases in activities that generally happen in the morning, like getting ready and partially eating, while earlier home trips were associated with increases in post-work activities like spare-time.

Conclusions

To summarize, based on this initial analysis, we can identify a clear division of the sample into several classes depending on the activity and travel changes. While a large proportion of the sample falls under the group that experiences little changes in their activity schedules, the different clustering distribution highlights common combinations of changes. The following main clusters were identified:

- **No change**: travelers in this cluster, which is the largest in the sample, make little to no changes to their travel and activities.
- **Work only on-board**: travelers in this cluster choose to transfer work tasks to travel episodes. As such, they tend to spend less time working outside of travel, and more time relaxing. They make little departure time changes as well.
- **Spare-time only on-board**: travelers in this cluster generally choose to use the traveling time to relax. This is also associated with more spare-time outside travel, and earlier home-bound travel.
- **All activities on-board, work**: this group of travelers does not have a single activity focus during travel, choosing to engage in all activities, but work remains the most significant one. As such, most activities that are increased on-board are decreased outside of travel, with the exception of spare-time. Earlier home-bound travel and delayed work-bound travel are also common changes.

- **All activities on-board, spare-time**: similarly, this group of travelers does not have a single activity focus on-board, but does engage in spare-time more often than other activities. Similarly, all activities are decreased outside of travel besides spare-time and sleep.

With this, we understand how on-board activities are associated with the rest of the schedule, stationary activities and departure times included. Nonetheless, questions concerning the motivations behind these schedule change decisions remain. Indeed, we believe that even in the case of the no-change clusters, the reasons behind not expecting any change in schedules are many. Whether it is seeking comfort and enjoyment during travel, or relieving pressure from the need to do many activities in limited time, each respondent values, or not, some benefit of autonomous vehicles over others, and that guides their expectations of how they would use them. Such insight cannot be inferred from the schedule change variables, as they are manifestations of these expectations. Rather, we look to individual and socio-economics characteristics, and travel specific features, as they are unique traits of individuals that condition how they value time, how exposed they are to technology. We speculate these factors would influence what people will value about autonomous vehicles, whether it is the comfort, safety, additional useful time that can used productively or for relaxing, or the novelty of technological innovation. Thus, including them in the clustering process will allow us to identify the link between the schedules and the individuals. To do so, the person-specific variables will be introduced as covariates. Besides the variables eliminated for redundancy reasons in section 5.1.1 before the logistic regression, all variables will be included in the analysis, as we are not only evaluating their significance, but also their usefulness and interpretability.

5.2.2 Clustering by Schedule Change Indicators and Individual Characteristics

Of these covariates, we make the distinction between active and inactive ones. Active covariates are ones that actively contribute to the model parametrisation. Of the variables available to us, we choose to include socio-economic factors (age, income, education...), some travel characteristics (currently preferred travel mode, frequency, average total travel time,), as well as other personal characteristics (motion sickness, daily time pressure...). Though it is part of the experimental setup and randomly assigned, the level of activity facilitation (partial or full) is included as an active covariate, as we expect it could be an influential factor on the time allocation to activities during travel. The inactive covariates are variables that we consider have some association with the indicators, but they do not actively alter the parameters of the model. As addressed earlier, to counter the biases introduced in the experiment resulting from travel time limitations, the duration and departure time changes were studied relatively to the total travel time. In this stage, we choose to include the average single trip travel time as an inactive covariate in order to explore schedule changes with the commute travel time as a reference based on which to interpret class membership and profiles. In addition, seeing as dimensions like time and distance traveled are not flexible in the schedules, variables like the expected frequency of AV usage[1] and travel behavior change[2] somewhat cover them, and allow for some insight on the expectations of the respondents. Thus, such variables can be included as inactive covariates.

1 This variable describes the number of times respondents expect they would use an autonomous vehicle (all trips, some, most...), see appendix A for detailed responses

2 This variable describes the changes in travel distance respondents expect an autonomous vehicle would bring (travel further and more often...), see appendix A for detailed responses

Table 15: List of Indicators and Covariates

Indicators	Active Covariates		Inactive Covariates
Getting Ready On-board	Gender	Self Driving Car Knowledge	Travel Time
Work On-board	Age Group	Daily Time Pressure	Travel Behavior Change
Meal On-board	Children	Motion Sickness	Expected AV Usage Frequency
Spare Time On-board	Education		Considering to buy an AV
Sleep Stationary	Income Group		
Getting Ready Stationary	Work Type		
Work Stationary	Travel Frequency		
Meal Stationary	Travel Mode		
Spare Time Stationary	New Technology Adaption Speed		
Work Trip Departure	Work In the Car		
Home Trip Departure	Activity Facilitation Level		

While they are continuous, the indicators are represented as ordinal variables in order to reduce the influence of outliers on class membership. As they are categorical variables, all covariates, active and inactive, are represented as nominal.

Stationary and On-board Activity Duration Change Model
Starting with the changes in activity durations, both on-board and outside, we observe that the optimal cluster number, found using the previously defined criteria, remains 5 (see table 16 and figure 15). Some clusters are similar to the ones identified in the first stage, such as the cluster with no-change (cluster 1, 55.9% of the sample), with mainly spare time on-board (cluster 4, 10.42% of the sample), and with mainly work on-board (cluster 5, 5.711% of the sample). Others are different, such as the new cluster with no change on-board, but with significant stationary activity and departure time changes (cluster 2, 15.97%), and the cluster with all activities on-board (cluster 3, 11.99%).

Table 16: Latent Class Profiles of the 5-class Solution with On-board and Stationary Activity Duration Changes, with Covariates

Indicators- Duration Change	**Cluster Size (%)**	55.91%	15.97%	11.99%	10.42%	5.71%
Getting Ready On-board	Mean	0.000	0.000	0.027	0.023	0.094
Work On-board	Mean	0.000	0.000	0.258	0.178	0.503
Meal On-board	Mean	0.000	0.000	0.211	0.000	0.000
Spare Time On-board	Mean	0.000	0.000	0.212	0.503	0.006
Sleep Stationary	Mean	0.000	0.039	0.130	-0.001	0.086
Getting Ready Stationary	Mean	0.000	0.024	-0.039	0.001	-0.109
Work Stationary	Mean	0.000	0.063	-0.096	0.003	-0.555
Meal Stationary	Mean	0.000	-0.012	-0.149	-0.001	-0.002
Spare Time Stationary	Mean	0.000	0.029	0.156	0.010	0.395

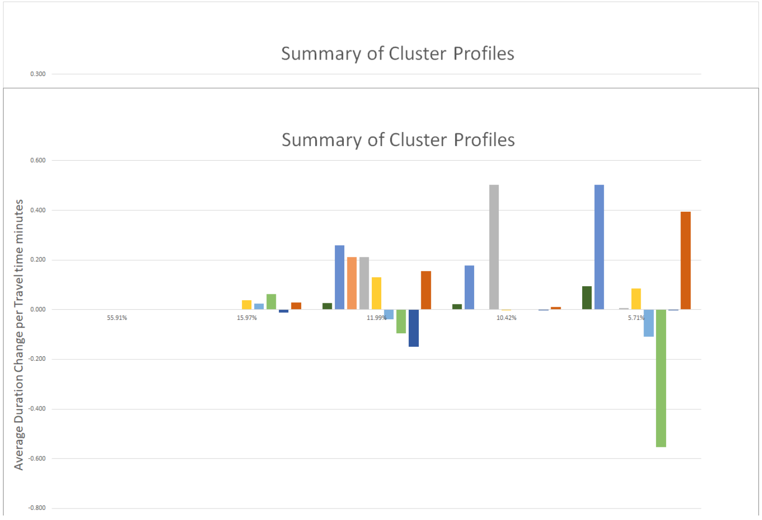

Figure 15: Summary of the Cluster Profiles with all Change Indicators (Model with covariates

Taking a deeper look into the covariates , we find that some provide insight into the heterogeneity between the clusters, while others lack significance. Starting with the latter, travel frequency, self-driving car knowledge, and work type are generally the same across the clusters, so they can be considered of low significance. To have further quantitative basis for this, we evaluate the p-value of the Wald statistic as generated by the software (see table 17). At a significance level of 5%, we see that education, the ability to do work in the car, and the daily time pressure are statistically significant[3]. Alternatively, knowledge of self driving cars, motion sickness and travel mode have a very high p-value, indicating little significance. Other covariates like daily time pressure and travel frequency have a p-value slightly higher than 0.05, but we will consider them in our analysis as the difference is not considerably large, especially in comparison to other covariates. To summarize the cluster profiles, table 18 below provides an overview of the most common responses in each cluster (see Appendix E for the full model).

Table 17: Statistical Significance of Active Covariates

Covariates	**Wald Statistic**	**p-value**
Activity Facilitation Level	3.03	0.540
Gender	4.5	0.330
Age group	5.6	0.230
Education*	38.6	0.030
Children	18.3	0.11
Income Group	23.3	0.280
Work Type	11.4	0.490
Travel Frequency*	9.03	0.060
Travel Mode	10.3	0.850
Daily Time Pressure*	24.2	0.079
Is Work Possible In Car**	31.4	0.001
Motion Sickness	7.5	0.820
New Technology Adaption Speed	11.7	0.16
Self Driving Car Knowledge	2.9	0.940

3 The p-value is <.05, so we reject the null hypothesis that the influence of these factors is zero

Table 18: Summary of the Cluster Profiles- Onboard and Stationary Activity Duration Change

	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**
Activity Facilitation Level	Partial	Partial	Ideal	Partial	Ideal
Gender	Men	Men	Women	Men	Men
Age Group	45-64	25-34/ 45-54	25-54	25-54	25-54
Education	MBO/ Bachelor	MBO/ Bachelor	MBO/ Bachelor	MBO/ Bachelor/ Master	Bachelor/ Master
Income Group	1-2x Average	1-2x Average	More than 2x average	1-2x Average/ More than 2x average	1-2x Average/ More than 2x average
Daily Time Pressure	Medium	Medium	High	Medium-High	High
Work In the Car	None/ Some of the tasks	Some/None of the tasks	Some/Most of the tasks	All/ Most/ Some of the tasks	All/Most of the tasks
New Technology Adaption Speed	Sometimes	Sometimes	Sometimes/ Almost never	Sometimes	Sometimes/ Often
Travel Time	10-30 mins	10-30 mins	30-60 mins	30-60 mins	30-60 mins
Expected AV Usage Frequency	Almost all trips/ Uncertain	Almost all trips/ Uncertain	Almost all	Almost all trips	Almost all trips
Intent to Purchase AV	Maybe/No	Maybe/Yes	Yes/ Maybe	Maybe/Yes	Yes

Members of cluster 1 are generally individuals between the ages of 45 and 64, with no children. Generally, they are employed in the private sector, and make 1-2x the average income. They tend to have difficulties doing work in the car, as most cannot do any work tasks during travel, with most of the rest being able to do only some. Furthermore, most experience medium time pressure. As for the inactive clusters, we see that many are significant. As mentioned earlier, we expect that short travel times could be a reason behind the lack of engagement in activities on-board. In this case, it is somewhat confirmed, as members of cluster 1 tend to have a short travel time, 10 to 30 minutes. As for the expected AV usage frequency, the majority, though small, seem to believe they would use an autonomous vehicle for all trips, which indicates interest in the technology, further hinting that the reasons behind the lack of engagement in activities on-board may be due to resource or work-specific limitations. However, when looking at the other responses, the distribution is quite even, indicating high heterogeneity within this cluster. Some of those are conservative in how often they expect to use an autonomous vehicle (13.4% think they would use one for many trips, 18.8% for some trips), others expect little usage (20.3% think they would use one for almost no trips), but there are also are many who are uncertain (13.4% do not know). The differences within the cluster are also apparent in the last covariate, as most are uncertain if they would consider buying an autonomous vehicle (38%), but around the same proportion believe they would not (34.4%).

Similar to cluster 1, members of cluster 2 (15.97% of the sample) also do not engage in activities during travel, but they do expect changes in stationary activity duration. Indeed, for every minute of travel, all stationary activities, aside from meals, are increased. Interestingly, their age distribution is slightly different from that of cluster 1, as the population of this clusters is slightly younger, with more being in the 25-34 range (27.9%), so most are either in that age range or the 45-54 range. Most other factors are comparable and nearly the same, with a few exceptions. The clearest one is the ability to do work in the car, which is improved in comparison, as more people are likely to be able to do some work tasks (41.7% against 32.2%). Additionally, travel time is slightly higher, with more people traveling for 30-60 minutes. While higher levels of uncertainty about the intent to purchase an autonomous vehicle are observed (41.8%), there are more respondents who would consider buying an AV (32.9%). Overall, this cluster is essentially one of respondents who are interested in autonomous vehicles, but are somewhat skeptical and conservative in how they expect it to change their lives. Members of cluster 3 engage in all activities during travel significantly, and expect to make modifications in their other stationary activities as well. While is the most common on average (25% of the travel time is spent working), meals and spare time are not far behind (both make up 21% of travel time use). This cluster is predominantly women between the ages of 25 and 54, with no dominant age group. They are generally highly educated, with most being at bachelor or master level. While,accordingly, they are in the highest income bracket (42% in >2x income range), we cannot consider this due to the lack of significance of income as a covariate. Time pressure is generally high for this group of travelers, and work tasks are more feasible in the car than in other clusters (39% canto do most work activities during travel, 40% can do some). As such, we can expect that these two factors are influential in driving the increase of work activities on-board. The longer travel times are conducive to this, as more than half of the population of this cluster travels for longer than 30 minutes. Nonetheless, the proportion of travelers who can do all work tasks in the car is very small (8.5%), thus many may not be able to spend all their travel time working, which could explain the variation in activities. Expected AV usage is less spread out than in cluster 1, as nearly half the population of this cluster think they would use an AV to for all trips capacity , and very few expect not to use it at all. While the uncertainty over using is much lower than in cluster 1, the uncertainty over buying an autonomous vehicle is still somewhat high. Though most of the respondents think they would consider buying an autonomous vehicle (44%), many remain uncertain (35.6%). Overall, this cluster represents a more enthusiastic group of travelers, who are more open to making full use of autonomous vehicles, as seen by the significant activity transfers to the vehicle.

Members of cluster 4 are mostly oriented towards spare time on-board. This cluster is composed of mainly men aged 25 to 54, many with at least MBO level education, though less are at the bachelor/master level. Their income levels are unevenly distributed, with high proportions of individuals below the average income (over 50% earing 1-2x average income or less), and a few above the 2x average income range (23%). In general, members of this cluster experience medium (47%) to high (29.3%) time pressure. The ability to do work tasks is also slightly higher in comparison to other clusters, as many can do all tasks (23.6%), most tasks (21.4%) and many tasks (34.5%). With such facilitation levels, we expect higher increases of work on-board, but the relatively medium level of time pressure, and high proportion of students in the cluster (13.7%) could hint that the need to work during travel is not as urgent, and that leisure and spare time are preferred. Additionally, With most respondents in this cluster having partial activity facilitation, it is possible that it was an influential factor in the decision to choose spare time activities during travel more than other activities. Travel time may also be an important factor, as a significant proportion travel 10-30 minutes (33%), though most still travel 30-60 minutes (51%). Overall, the expected usage of AV paints a positive image, as most would use an AV for nearly all their trips, or at least many trips. While the interest is high, the intent to purchase an autonomous vehicle is less clear. Indeed, most of the respondents are uncertain about considering to buy an autonomous vehicle (41%), though 35% would consider it. This could possibly be related to income disparities, as over half of the population earns 1-2x the average income or less. Comparatively, in cluster 3, where most respondents would consider buying an AV, 42% earn more than 2x the average income. Furthermore, as this cluster has the lowest proportion of travelers who often try new technologies (17%), exposure and trust in new technologies may make them more reluctant to invest in it.This difference also hints that members of this cluster may prefer ride sharing autonomous vehicles over owning a vehicle themselves.

The work oriented travelers are in cluster 5, as they transfer work activities to the travel episodes, using over half (50.3%) of their travel time working, and freeing up time for more spare time and sleep outside travel. The members of this cluster are generally men aged 25 to 54, with high education levels (bachelor, master/doctoral). Most are employed in the private and public sector, and hardly any are student. As a result, most are part of high income ranges, (32% in the 1-2x the average income). As such, this cluster is a highly educated affluent group, which is reflected in the new technology adoption speed (36% tend to try new technologies often, the highest of all clusters), as well as in the expected frequency of usage (75% think they would use an AV for all their trips). Furthermore, the majority of members of this cluster (68%) would consider purchasing an autonomous vehicle, confirming that individuals with more disposable income would be more prepared to own an AV. Time pressure seems to be associated with more work activities during travel, as 53.6% of the members of this cluster are likely to experience high time pressure. Considering the work type distribution, we believe that time pressure is associated with high income employed individuals. With high time pressure grows the need for transferring activities to the travel episode with the goal of relieving some of that pressure. In this case, as more than half of the members of this cluster can do at least most work tasks in the car (32.1% can do all, 32.2% can do most), and the travel time was long enough (53% travel for 30-60 minutes, 14% for more than 60 minutes), work was prioritized. We can then assume that daily time pressure is mostly driven by work pressure, as members of cluster 4, also experiencing a significant transfer of spare time activities to the travel episodes, do not experience nearly as high time pressure. As such, this highly educated, working group of travelers is one that is mostly interested in using autonomous vehicles to use the travel time productively for work tasks, relieving work-related pressure and freeing up time for relaxing and leisure.

Travel Departure time, On-board and Stationary Activity Duration Change Model
Combining all three types of indicators, the optimal number of cluster is 5, see table 19 and figure 16. The addition of travel departure time reverts the cluster distribution to the original distribution without covariates. Aside from the no-change cluster, again the most populated at 44.22% of the sample, the distinction of on-board activities splits the clusters into single activity focused ones (clusters 2; 18.6% of the sample, and 3; 17.6% of the sample), and multi-activity ones, cluster 4 (11% of the sample) and 5 (8.6% of the sample). Of the single activity on-board clusters, cluster 2 is focused on work, as work activities are transferred to the travel episode, allowing more time fore leisure and spare time. Cluster 3, on the other hand, is spare time focused, while also experiencing the largest change in departure time, with significant advancement of homebound trips and delay of work-bound trips. The other two clusters show more variety, as all activities are significantly increase during travel. In the case of cluster 4, spare time is most common on-board, while work is more common in cluster 5. The addition of covariates changes the clustering considerably, especially in terms of the departure time changes, which are significant for only clusters 3,4 and 5.

Table 19: Latent Class Profiles of the 5-class Solution with On-board, Stationary Activity Duration and Departure Time Changes, with Covariates

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Indicators	**Cluster Size (%)**	44.22%	18.57%	17.58%	11.05%	8.58%
Getting Ready On-board	Mean	0.000	0.000	0.000	0.000	0.128
Work On-board	Mean	0.000	0.184	0.000	0.274	0.166
Meal On-board	Mean	0.000	0.000	0.000	0.185	0.059
Spare Time On-board	Mean	0.000	0.000	0.251	0.089	0.262
Sleep Stationary	Mean	0.000	0.054	0.000	0.097	0.066
Getting Ready Stationary	Mean	0.000	0.033	0.000	0.016	-0.159
Work Stationary	Mean	0.000	-0.047	-0.001	-0.137	-0.114
Meal Stationary	Mean	0.000	0.006	-0.001	-0.131	-0.074
Spare Time Stationary	Mean	0.000	0.100	0.006	0.139	0.138
Work Trip Departure	Mean	0.000	0.001	0.024	0.074	0.007
Home Trip Departure	Mean	0.001	0.000	-0.121	-0.062	0.004

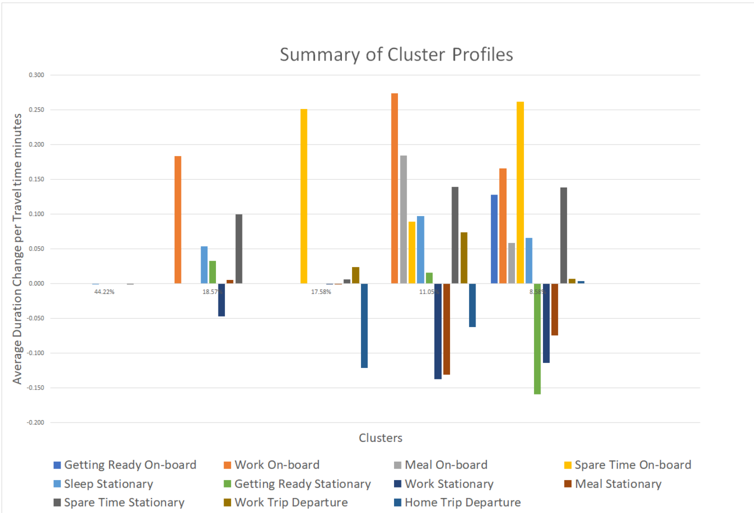

Figure 16: Summary of the Cluster Profiles with all Change Indicators (Model with covariates

At a significance level of 5%, we see that education, time pressure, and the ability to do work in the car are statistically significant, with gender being slightly above the threshold of significance (see table 20). Similarly to the first model, knowledge of self driving cars and travel mode are found to have little significance, along with motion sickness to some extent. To summarize the cluster profiles, table 21 below provides an overview of the most common responses in each cluster.

Table 20: Statistical Significance of Active Covariates

Covariates	Wald Statistic	p-value
Activity Facilitation Level	6.1	0.190
Gender	7.8	0.099
Age group	25.4	0.180
Education**	44.4	0.007
Children	15.8	0.200
Income Group	26.3	0.160
Work Type	15.3	0.220
Travel Frequency	7.4	0.120
Travel Mode	10	0.870
Daily Time Pressure*	25.5	0.060
Is Work Possible In Car**	36.2	0.000
Motion Sickness	11.5	0.480
New Technology Adaption Speed	11.7	0.160
Self Driving Car Knowledge	2.01	0.980

Table 21: Summary of the Cluster Profiles- On-board, Stationary Activity Duration and Departure Time Change

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Activity Facilitation Level	Ideal	Ideal	Partial	Ideal	Partial
Gender	Men	Men	Men	Women	Women
Age Group	45-64	25-34/45-54	35-64	25-34/45-54	25-54
Education	MBO/Bachelor	MBO/ Bachelor/ Master	MBO/ Bachelor	Bachelor/Master	Bachelor/Master
Income Group	Average / 1-2x Average	1-2x average / More than 2x average	1-2x Average	More than 2x average	Average / 1-2x Average
Daily Time Pressure	Medium	Medium-High	Medium	High- Medium	High
Work In the Car	None/ Some tasks	Most/ Some/ None of the tasks	Some/ None of the tasks	Most/ Some of the tasks	All/ Most/ Some of the tasks
New Technology Adaption Speed	Sometimes	Sometimes	Sometimes/ Seldom	Sometimes	Seldom
Travel Time	10-30 mins	10-30/ 30-60 mins	10-30 mins	30-60 mins	30-60 mins
Expected AV Usage Frequency	Almost all trips/ Uncertain	Almost all/ Many trips	Almost all/ Almost no trips	Almost all/ Many trips	Almost all trips
Intent to Purchase AV	Maybe/No	Yes/ Maybe	Maybe	Yes/Maybe	Yes/Maybe

Overall, the personal characteristics are consistent with the initial analysis from the previous sub-models. Indeed, the first cluster, with hardly any schedule changes, is mostly composed of men aged 45 to 64, with MBO or bachelor level education. Similarly, they do not feel high time pressure (54% feel medium pressure), and most cannot do any work tasks in the car (43%), which could explain the lack of work activities during travel. Additionally, their travel time is the lowest (59% travel 0-30 minutes), which is in line with our earlier expectations that short travel times do not allow much freedom in activity engagement on-board. This group of traveler is also one that is undecided (37%) or is not considering (35%) to buy an autonomous vehicle, which is associated with a relatively average income (20% earn average income, 39% earn 1-2x the average income). This uncertainty is also reflected in the expected usage frequency, as this cluster has the lowest percentage of individuals who think they would use an AV for all their trips (35%), while all other responses are nearly equally represented. Indeed, up to 14% are uncertain about how often they would drive an AV, while 15% think they would use it for many trips. As mentioned earlier, this heterogeneity highlights that there are different reasons that justify the lack of significant change in the schedules. But, we can hypothesize that this group of travelers ties the value of autonomous vehicles to the ability to do work activities during travel. Since most cannot do most of their work on-board, the interest in owning or using an AV is low. A very small proportion of these travelers have limited knowledge of AVs, but since most do know about them and this metric is highly insignificant as mentioned earlier, we can assume that this disinterest does not stem from lack of knowledge. In addition, since most travelers have a short travel time (10-30 minutes), they may see this as insufficient time to engage in activities constructively, so they do not find value in having the ability of doing activities during travel if the travel time is short.

Members of cluster 2, however, are travelers who do engage in work activities during travel, with the goal of freeing up time for relaxing and leisure outside travel. Though, in comparison to the same cluster without the departure time changes, the magnitude of change is smaller, as travelers here use up to 18% of their travel time for work, in comparison to 50% in the previous model. However, we must point out that this cluster is much larger, indicating that many other responses with smaller increases of work on-board were allocated to this cluster. Again, men are more represented, but this group is much younger, with most being in the 25-34 range, and slightly less in the 45-54 range. The level of education is similar to the first cluster, though a few more are at the master/doctoral level (20.9%). Time pressure is higher for members of this cluster (36% experience high time pressure), which supports the initial finding that high time pressure drives transferring work tasks to the travel episodes, in association with work task facilitation and travel time. Indeed, most members of this cluster can do at least some work activities in the car (22% can do most, 34% can do some), and less are not able to do any tasks (30%) in the car in comparison to the first cluster. As for the travel time, it is overall longer than that of cluster 1, with more people having travel times higher than 30 minutes (43% travel for 30-60 minutes against 33% in cluster 1). These characteristics seem to support positive interest and perception of autonomous vehicles, which is reflected in the expected frequency of usage, as nearly 50% of the members of this cluster expect they would use one for almost all their trips, and most would actually consider buying one (38%). Nonetheless, the same amount of travelers (38%) are also uncertain about purchasing an autonomous vehicle. Overall, similar to cluster 1, this is also a group of travelers who are mostly interested in autonomous vehicles for the prospect of engaging in work activities during travel. Unlike the first group, the circumstances of their work and travel are more conducive for on-board work, as the type of work they do allows them more flexibility for remote work and their travel time is longer. Further, the demand for the additional time to use for work activities is higher for this group, as they are under higher time pressure, and need time to relax (reflected in the increase in stationary spare time duration).

Cluster 3 is composed of travelers who use the travel time for relaxing and leisure mainly. Similar to previous models, the prevalence of spare time on-board is often associated with limited changes in stationary activities, with only spare-time increasing, and meals and work very slightly decreasing. The other major schedule change is a significant advancement of home-bound trips, which is in line with our initial expectations that an increase in spare time in a schedule is associated with earlier home-bound travel. On the other hand, work-bound travel is delayed on average. The members of this cluster are mostly men between ages 35 and 64, with MBO (30%) or bachelor level (34%) education. Their income is around average and slightly higher (45% earn 1-2x the average income). Most experience medium to low time pressure and can do some work tasks in the car (35% can do some tasks), though many have difficulties doing any (36% cannot do any work tasks in the car). As such, it is evident that work on-board is difficult for them, but also not necessarily needed, as time pressure is not particularly high.

Furthermore, as the majority have partial facilitation, respondents may think that spare time activities do not require full facilitation, while work activities require more focus and facilitation. Additionally, travel time is somewhat short, as 51% travel 10-30 minutes, and most (81%) expect they would not travel further. An interesting distribution is the expected frequency of usage, as most respondents believe they would use an AV for almost all trips (38%), but a considerable percentage expects to use it for nearly no trip (23%), and many are also uncertain about their expected usage (0%). Additionally, most respondents are also uncertain about buying an autonomous vehicle (45%), which may be due to their average income in comparison to other clusters. We can conclude that this is a group of travelers who believe they could benefit from autonomous vehicles to relax, but would not really consider them for much else, i.e work, and they do not expect it would have a big impact on how they schedule their day. That may be due to limitations related to their work type, which does not allow them to do much work in the car. As such, we can hypothesize that the value of autonomous vehicles for them is not tied to the possibility to do work, but rather the enjoyment of the traveling experience and the elimination of the stress associated with the driving responsibility.

Members of cluster 4 engage in all activities during travel, with work being the most common. It is composed of women aged 25-54, also highly educated (bachelor/master level). The majority are employed in the private sector (64%), while many being entrepreneurs as well (14%). As such, the time pressure they experience is generally high (45% experience high time pressure, 41% medium), which, as found earlier, drives the need for additional time for work. Considering over 34% of travelers can do most of their work tasks in the car, and their travel time is long (49% travel 30-60 minutes, 15% travel more than 60 minutes), engaging in work activities in the car is possible, and significantly needed by this group. With the long travel times, we expect that these travelers choose to engage in more than one activity per trip. Indeed, considering the duration of meal time and getting ready during travel is higher, while these activities are reduced outside of travel, we expect that this group of travelers tend to use the duration of the work-bound trip to eat and get ready, and possibly work. Overall, the expectations of autonomous vehicles are quite positive, with most thinking they would use an autonomous vehicle for all trips (39%), and many thinking they would for at least many trips (24%). 43% would consider buying an autonomous vehicle, which matches our expectation that high income individuals would be more open to purchasing an AV. Furthermore, considering that many members of this group are exposed to new technologies regularly (27% try new technologies often, 42% sometimes), we believe they are more prepared to accept autonomous vehicles and make full use of them. Additionally, this group of travelers is one of the least "uncertain", as it has the second smallest proportion of individuals who are not certain of how often they would use an autonomous vehicle (3%), and if they would buy an autonomous vehicle (33%). Overall, this group of travelers is similar to cluster 2 in that they are mostly interested in using AVs for work activities, with the difference being that they are more open to using it for other activities if they cannot, or do not want to, do work tasks.

Similarly to cluster 4, cluster 5 is one in which all activities are undertaken during travel, though spare time and work are most common. They are also mostly women aged 25 to 54, with high education levels (bachelor/master or doctoral), though many are at the MBO level (21%). Most are employed in the private sector or the government, but there is a high proportion of students (11%), which could explain the presence of low income respondents (15% earn below average income). The majority still earn average to slightly more than average income (31% earn 1-2x the average income, 20% earn more than 2x the average income). Time pressure is generally high (53%), and most can do at least some of their work activities in the car (and 29% can do all work tasks in the car), which explains the increase in the duration of work in the car. However, as up to 15% cannot do any work tasks in the car, work-on board might be limited to a certain proportion of the group. Nonetheless, the travel time is mostly in the 30-60 minutes range (46%), which provides more opportunities to engage in activities. While work would seem to be the most likely, especially for the older employed population, we think the high proportion of students drives the increase in spare time duration, as most students may not be able to do any work tasks during travel, so they would tend to engage in other activities. Evidently, the members of this cluster are interested in using autonomous vehicles, as 62% expect to use one for all their trips, with the rest expecting it for at least many trips. Interestingly, half of the members of this cluster (51%) almost never try new technologies, which could indicate limited exposure or openness to innovations, but nearly all know about autonomous vehicles, and most are open to buying one (44%). This could indicate that the novelty of autonomous vehicles and its attraction as a new innovation is not an important factor behind this group of travelers' interest in AVs. Rather, we think it is activity facilitation, and the possibility to engage in various activities, mostly spare time and relaxing, but also work if needed.

Conclusion and Discussion

From this analysis, it is clear that personal characteristics and socio-economic factors influence the propensity to engage in activities during travel and introduce travel and stationary activity rearrangements in different ways. To understand these effects, we distinguish different levels of influence. Some attributes provide the base profile of individuals who would be interested in using an autonomous vehicle, by positively influencing intent to use. As such, educated individuals are more likely to positively perceive autonomous vehicles and their benefits, and thus, would be more enthusiastic about using them. Another such attribute is time pressure, as it drives the need for additional useful time, mostly to be able to engage in work activities to relieve that pressure. This reflects not only in the intent to use indicators (expected AV usage frequency), but also in the schedules, with significant on-board and stationary activity changes, and travel as well. While income was especially associated with the intent to buy an autonomous vehicle, as richer individuals were more open to it, we cannot claim that the association is significant due to the limited significance of this metric. Consistent with the findings of the logistic regression, most socio-economic factors were not significantly associated with schedule changes. Gender was generally non-significant, though its significance improved in the model with travel departure time changes. Nonetheless, it was apparent that in the case of travelers who engaged in multiple activities on-board, more individuals were women, hinting that multitasking may be more likely with female travelers. In the two clusters of concern, respondents have more children in comparison to others, so it is possible that the additional responsibility of taking care of children, which is generally undertaken by women, increases time pressure, making using the travel time for activities more attractive.

It was expected that exposure to and knowledge of new technologies would be significant in making individuals more prepared and open to making full use of autonomous. However, knowledge of self driving cars was found to be insignificant, as the vast majority of the sample had knowledge of AVs, even those who reported no schedule changes. As such, we can conclude that, as the current situation stands, base knowledge of autonomous vehicles is prevalent. On the other hand, the influence of new technology adoption speed was slightly more difficult to assess, as instances of travelers with high adoption speed reported no changes in schedules, while others with comparable responses reported a wide array of activity and travel changes. As such, we speculate that this factor influences in association with other attributes or variables.

However, we believe these base attributes are not sufficient to materialize the interest in autonomous vehicles into schedule changes, as other contextual attributes can act as barriers. Indeed, as identified, longer travel times are generally conducive to activity changes, so travel time cam limit the extent to which individuals make use of autonomous vehicles, regardless of their interest and intentions. Another critical "barrier" attribute is the ability to do work in the car. As work is one of the most prevalent activities during travel, the extent to which individuals can transfer work tasks to the vehicle was found to be a significant factor influencing the scheduling process. Not all jobs allow remote work, and resource and coupling constraints can significantly limit the work tasks possible in the car. Therefore, if the interest in using autonomous vehicles is only to be able to engage in work activities during travel, no changes would be observed at all, and the initial intent to use may not be as significant.

Other variables relate to the comfort and conditions inside the vehicle, one of which being activity facilitation. Though expected to be much more significant, on-board activity facilitation's effect on the types of activities during travel was clear. Ideal facilitation was found to be often associated with more work activities on-board, while partial facilitation with spare time. Travelers might believe that partial facilitation does not provide the environment and comfort necessary to engage in activities requiring focus like work, so relaxing was preferred. Nonetheless, we speculate that activity facilitation was more of a secondary conditioning predictor, which is reasonable considering the lack of experience with real autonomous vehicles, so understanding the effects of partial and full facilitation on the ability to do activities remains subject to the interpretation of the travelers themselves. Finally, motion sickness was , again, found to have limited influence on the ability to engage in activities during travel, and on the interest in using autonomous vehicles in general. Though, it must be pointed out that nearly 80% of the sample reported to never experiencing motion sickness, so low representation of individuals who do may have infused some biases in the data. Nonetheless, there was no indication of significant influence, even in clusters with high proportions of individuals experiencing motion sickness in some way.

5.2.3 Synthesis

In this chapter, we have explored the factors influencing schedule rearrangements. With insights from an initial logistic regression estimating the influence of individual characteristics on the occurrence of activity and travel changes, we expanded the rearrangement indicators to include specific activity and travel changes. With that, we tried to identify heterogeneous groups within the population with significant differences in schedule rearrangements.

Starting with a logistic regression, we found that the binary occurrence of changes to activity schedules is difficult to predict with the variables at our disposal. Of the socio-economic factors, gender and education were found to be good predictors of the occurrence of on-board activity change, while only income was found to have some influence on stationary activity and travel changes. As for travel characteristics, the initial expectation that longer travel times were more conducive for productive travel time was confirmed to some extent, but it was also found that longer travel times contributed to stationary activity changes. As for travel changes, the frequency of travel was more influential, as less frequent travel increased the probability of a travel change occurring. Other personal characteristics were slightly more influential, as and the ability to do work activities in the car were identified as significant predictors of the occurrence activity-travel changes. Motion sickness and time pressure, however, emerged as insignificant indicators.

As the results of the logistic regression provided confirmation for some initial expectations, and denied others, we concluded that the specific schedule rearrangements must be explored individually using latent class clustering models. The resulting classes match the initial classifications from chapter 4, with three main changes to be distinguished: no-change, single activity on-board (work and spare time), and multiple activities on-board. In the clusters with multiple activities during travel, all activities were increased, but either one of work or spare time were more significantly increased. Direct activity transfer was common with work, meals, and getting ready, but less with spare time. Indeed, more often than not, spare time on-board was often associated with more spare-time outside travel. As such, we identified that there were significant interactions between on-board and stationary activities, though the direction of these relationships remain unknown. As for travel changes, the most significant changes, earlier home-bound travel and delayed work-bound travel, were mostly observed in the spare-time only on-board cluster as well as the multi-activity on-board (mostly work) cluster.

We found that personal attributes and travel characteristics influence schedule rearrangements in different ways. While we cannot make conclusions about the intensity and direction of causal links, we can conclude the existence of strong and significant associations. Overall, socio-economic factors were not significant indicators, though some associations were observed.

Gender, the number of children in a household, income were all insignificant factors, while only education was significant. As such, a strong association between education and the intent to purchase an autonomous vehicle, as well as activity changes. Other personal characteristics were found to be more statistically significant. Indeed, daily time pressure was found to be a driver for work-on board, as most travelers with medium to high time pressure engaged in work during travel, and spent more time on leisure and spare-time outside travel. As expected, groups of travelers who engaged in work on-board generally worked in jobs that allowed remote work task facilitation, i.e many were able to do work activities in the car. Travel time generally supported engaging in more activities on-board, as members of the multi-activity on-board clusters often had the longest travel times. Similarly to what was found in the logistic regression, motion sickness was found to have little influence on scheduling decisions, even in clusters with significant changes (the multi-activity on-board clusters).

Finally, we can conclude that, according to expectations from this research, the schedule rearrangements in the autonomous vehicle era are not as dramatic as speculated in the literature. Most respondents reported little changes in their schedules, and in general, their expectations remain conservative. Across all clusters, few expect to change their travel frequency and the distance traveled, while the intention to purchase autonomous vehicles was often highly uncertain across all groups, even the most enthusiastic and affluent ones.

6 CONCLUSIONS

This thesis has examined the possible impacts of autonomous vehicles on travel behavior using various quantitative methods, and in turn has identified different factors influencing certain effects and uncovered interactions between different components of activity-travel schedules. Using these insights, we can reflect on the research questions and objective stated in the introduction.

This chapter will begin by providing answers to each research question, including a reflection and discussion of the policy implications of this research. Then, we will discuss our findings in the context of existing research, and report possible limitations. Finally, recommendations for future work will be provided.

6.1 DISCUSSION AND RESEARCH QUESTIONS

The two results chapters (chapters 4 and 5 addressed the first two research questions). In this section, we will provide answers for these questions.

RQ1. What types of rearrangements in travel patterns and activity schedules are expected to emerge with the introduction of autonomous vehicles?

Starting with our initial exploration of the survey data, we were able to identify major streams of activity and travel changes. Indeed, as we explored activity changes, we distinguished between two types: *on-board activity changes*,which describe changes of activities during travel, and *stationary activity changes*, which describe changes of activities outside travel. Work and spare-time were identified as the main activities that increased in duration on-board, with meals and getting ready being common as well, but less significantly. As for stationary activities, work, spare-time, meals, getting ready, and sleep were found to be the most significantly changed. Of the latter changes, work, meals, and getting ready were often reduced outside travel, while sleep and spare-time increased.

As for travel changes, we found that the frequency of travel remained mostly unchanged, with the number of trips mostly staying constant, aside from the occasional trip elimination. This was consistent with what we initially expected from the literature review, as research has identified the difficulty in adding and eliminating trips. Furthermore, later examination of survey responses, one of which included a question concerning the expected changes in traveled distance and frequency, uncovered conservative expectations, as most respondents did not expect to travel more frequently and/or further. However, we did identify travel departure times as significant rearrangements. Indeed, as all the respondents were commuters, students and employed individuals, work-bound trips and home-bound trips were found to be most influenced. Trips to work were mostly delayed, while home-bound trips were advanced. We expect that this would be related to the newfound activity facilitation during travel, which would allow travelers to engage in activities on-board, and have more flexibility in when they choose to travel without losing out of "useful" time.

Looking deeper into combination of these changes, the latent class clustering uncovered some common joint changes. The most commonly found in the data was the transfer of work activities to the travel episode. Other activities like meals and getting ready were often also transferred. The same could not be said for spare-time, however, as it often increased both in the vehicle and out of it. We interpreted this as a need for leisure time that could not be satisfied in the schedules as they were, so the additional useful time on-board provided more opportunities for travelers to relax, which they did not have before.

Finally, as we clustered the respondents using travel and activity change indicators (travel departure change and activity duration change), we identified five main clusters: *No change, only work on-board, only spare time on-board, multiple activities on-board (work and spare-time).* The findings of the initial data exploration were confirmed, as the segmentation of the sample was according to the same general activity change streams, no schedule change, and work and/or spare-time on-board. The clusters in which multiple activities on-board increased were also dominated by one of these two activities. Further, we found that the advancement of home-bound trips was often associated with an increase in spare time, which we speculate could be attributed to spare-time being mostly a post-work activity, so an earlier return home provides more time to spend on leisure.

Through this research, the inter-dependencies between travel-activity choices have been highlighted, as associations between all types were observed, though the direction of these relations remains unknown. Indeed, we observed activity transfer to travel episodes, for instance for work, but we are not certain if work tasks have been moved to the travel episode and led to time being freed up for another activity, or if said activity was scheduled first, forcing work tasks to be moved. Nonetheless, it is clear that the different components of activity-travel schedules are inter-dependent, and that these dependencies influence the behavioral changes of individuals.

RQ2. What factors and characteristics of travelers are associated with the specific activity schedule rearrangements?

To answer this question, we began with a logistic regression to identify possible predictors of the binary occurrence of schedule changes on three levels: *on-board activity change, stationary activity change, travel change*. This included all types of changes, not only the most common, which were durations for activities and departure times for travel. The indicators used as possible predictors were: socio-economic factors, travel characteristics, and other personal attributes.Three models predicting each of the three binary change variables were estimated.

The results of the logistic regression models showed that socio-economic factors were limited in their predictive ability. Women and highly educated individuals were found to be more likely to engage in activities during travel. However, no socio-economic factor was significant in predicting stationary activity changes. Only income was found to be a significant predictor of only travel changes, but the observed effect was counter-intuitive, as higher income individuals were less likely to make changes to travel. Travel characteristics were found to be more influential, as we observed that longer travel time were conducive to more on-board and stationary activity changes, while less frequent travel increased the probability of travel changes. We find that the ability to do work in the car is a significant predictor of both activity changes, although the influence mostly comes from the extreme "no task is possible" responses. Indeed, we observe that when travelers can do work tasks in the car, regardless of the extent to which they can (some, most or all), the effect on the likelihood to engage in activities on-board or change stationary activities is not much different. If they are not able to do any tasks, the likelihood is dramatically decreased. Daily time pressure and motion sickness were found to have no significant influence on any of the travel changes.

However, the logistic regression models were limited, as they only allowed us to explore the influence of the individual characteristics on the occurrence of changes in general, rather than the choices to make specific changes. As such, adding these indicators as covariates to the latent class models, which had uncovered classes of schedule rearrangements, allowed us to explore the influence of each indicator on the single activity and travel changes. Additionally, indicators that were not used as predictors in the logistic regression models (the intent to purchase an autonomous vehicle, the expected AV usage frequency, the expected change in travel frequency and distance) were included as inactive covariates, so the associations between these variables and the indicators could be examined.

One of the main findings made is that some of the non-significant indicators have strong associations with activity-travel changes, but only to some specific ones, which explains why that influence was not captured in the logistic regression, in which all changes were aggregated. Though insignificant, income had a moderating effect on the intent to purchase autonomous vehicles, as more affluent individuals were more open to buying an AV, while less rich groups of travelers were rather uncertain about it. Nonetheless, socio-economic factors were confirmed to have limited significant associations with the various schedule changes, with only education proving to be significant enough to be considered. As such, groups of travelers who engaged in activities during travel, especially work, were often highly educated individuals. On the other hand, daily time pressure, which was found to be insignificant in the logistic regression, was identified as associated with changes in work activities, especially increases in work on-board. The combination of high time pressure with the ability to do work tasks in the car was significant in work focused schedules. Therefore, we conclude that the personal characteristics that control the context and ability to engage in activities on-board are the main factors associated with activity schedule changes.

As for characteristics of comfort on-board, motion sickness was confirmed to have little influence on any activity or travel change. Several researchers have highlighted motion sickness as a possible barrier that could hamper activity facilitation on-board and make multitasking during travel more difficult and less attractive [38][18]. Based on our findings, we believe that instances of motion sickness acting as an obstacle to engaging in on-board activities are not as significant as expected. Though we cannot necessarily claim that motion sickness has no influence on multitasking on-board and activity facilitation, as 80% of our sample reports never experiencing motion sickness, we do believe that further exploration of these effects at an individual level is needed.

A final observation was concerning the intent to purchase autonomous vehicles. Across all the classes of travelers identified, the skeptics and enthusiasts alike, the general trend was average to high reluctance to considering buying an autonomous vehicle. We observed that travelers who preferred spare-time only during travel were significantly more uncertain about owning an autonomous vehicle. We believe that such preference would make this group of travelers more open to shared autonomous vehicles rather than personal vehicles, which has consequences on the estimated effect on travel behavior, especially the vehicles-mile traveled. Thus, it may be valuable to consider these interactions in research assessing the overall impacts of autonomous vehicles on travel behavior.

Finally, thinking back to the expected effects of autonomous vehicles on travel and the value of time, we have observed that travel demand is not expected to increase, with only changes in departure times possibly influencing overall demand. The frequency of travel and the distance traveled, however, would not be significantly influenced. As research assumes that autonomous vehicles would decrease the value of travel time, thus leading to more travel, our findings lead us to believe that this influence is not as straightforwards as anticipated. Though we cannot make inferences on the actual effect of autonomous vehicles on the value of travel time, we can conclude that it is not a sufficiently comprehensive metric to capture the complex relations between on-board activities, travel choices, and activities outside travel. As such, our research provides an initial contribution to alternative activity-focused approaches to studying the impacts of autonomous vehicles on travel behavior.

6.2 Policy implications

With the understanding we have gained from exploring the schedule, we can expand on potential implications to policy, starting with the expected larger impacts autonomous vehicles could bring, to the limitations of traditional assessment methods that guide policy decisions.

6.2.1 Higher Order Impacts of Autonomous vehicles

Based on our findings, we can expand on the potential larger impacts of autonomous vehicles. Going back to the diagram of the different levels of ripple effects by Milakis, Arem, and Wee [49], we can discuss some potential effects that could emerge as consequences of the changes we have identified.

One of the main expected benefits of autonomous vehicles is the improvement of traffic efficiency, resulting from the reduction of human errors and the optimization of the driving process. However, as autonomous vehicles are generally expected to increase traffic efficiency, more demand for travel is induced, increasing the distance traveled by personal autonomous vehicles [22][11]. Even in literature exploring the impacts of shared autonomous vehicles, the expectation is generally the same [56][28]. However, based on our analysis, the general expectation of the majority is that they would make little modifications to their travel preferences. That is, the number of trips they would take and the distance they would travel are expected to remain the same. This reluctance to dramatically change travel may be due to the sample covering commuters only, so the impact of autonomous vehicles could be studied only with regards to daily trips, excluding occasional long distance trips. Nonetheless, as large increases in distance traveled would not be possible without significant changes in regular daily trips, we speculate that the evident reluctance to travel more and farther indicates the increase in VMT may not be as large as expected. Zmud and Sener reached a similar conclusion, finding that most individuals would not change their travel habits, and that most of the VMT increase would come from the addition of long distance travel [88]. Therefore, based on our analysis, we cannot claim that the advent of autonomous vehicles would induce more travel, at least not commuter travel. What is possible is that demand for long distance travel would increase as the value of engaging in activities during travel would make the trip more constructive. Further research is needed to identify the magnitude of this impact.

Nonetheless, that is not to say commuters did not expect any changes with regards to their travel behavior, as an important change in travel preferences that emerged was the shift in travel departure times. A significant pattern was the advancement of home-bound trips and delay of work-bound trips, especially by individuals who work during travel and spend more time relaxing after work. As such, we believe there is significant potential for a reduction of congestion in both the morning and evening peak hours. However, this is highly dependent on the characteristics of the individual travelers, as such patterns were only observed in association with other activity changes.

In this sample, most individuals were uncertain, and many not enthusiastic, about purchasing an autonomous vehicle. Limitations in income could have a role to play in this, but even in affluent groups of travelers, the uncertainty was significant. On one hand, this could indicate that the pessimistic scenarios for penetration rates would be more likely, and traditional vehicle ownership would not decrease significantly. On the other side, this reluctance could indicate a higher interest in shared autonomous vehicles, which could decrease the overall vehicle ownership,. Furthermore, as found by Spieser, Treleaven, Zhang, *et al.* in a Singapore case study, average penetration rates of shared autonomous vehicles would reduce the fleet size on the road by a third [73]. Therefore, we speculate that autonomous ride-sharing would be a preferred mode of transport for the individuals hesitant to purchase an autonomous vehicle. However, going back to the expected traffic effects, an increase in shared-vehicle travel demand would increase the total VMT by a single vehicle, as empty rides to pick up the next passenger or find a parking space would have to be considered. This could reflect in higher congestion levels, especially during peak hours, assuming no increase in road capacity, as addressed by Maciejewski and Bischoff in [44].

6.2.2 Limitations of the Travel Time Penalty Approach

One of the main findings of this research is that travelers are generally conservative in how they expect their travel behavior will change as a result of autonomous vehicles. Indeed, we believe that, in the case of commuters, autonomous vehicles will have more influence on travel departure times than on the number of trips. Though distance traveled could not be explored in detail as part of the schedules, the general expectation gathered was that travelers would not travel further or for longer time. As limited and contextual as this insight is, considering our sample is composed of commuters only, whose trips are largely rigid, we do believe that the distance traveled in daily schedules would be difficult to change significantly. Therefore, we speculate that the expectations of increased VMT, which literature claims, may be too optimistic. Furthermore, considering the aforementioned general reluctance to consider purchasing autonomous vehicles, it is possible that many travelers may prefer shared AVs, which would have significant consequences on traffic. As such, the ripple effects of autonomous vehicles, as per the framework [49], would be estimated differently. Considering insights from the assessment of these impacts are used as a basis for policy making, including significant infrastructure investment decisions, more research is required to accurately assess all potential travel behavior changes, considering different scenarios and population segments.

However, we believe that it is not the results themselves that indicate possible limitations in current research, but rather the approach we have selected to assess travel behavior changes. Indeed, this research has highlighted the immense complexity in the AV-driven travel and activity pattern changes, not only in the wide scope of possible changes, and combinations of rearrangements, but also in the factors influencing them. Not only do intrinsic individual attributes, characteristics, and preferences contribute to the modification of these pattern, but the components of the schedules themselves activity and travel fragments strongly influence each other. Indeed, the choice of engaging in activities during travel can have repercussions on travel and stationary activities, just as stationary activities can drive the choice of on-board activities. Though we could not identify the direction of this relationship, we did observe instances of certain types of changes occurring in combination e.g increase in work on-board with a reduction of work outside travel, increase in spare-time on-board with earlier home-bound trips.

Based on this, we believe that the process of scheduling travel and activity is intricate and complex, and using an assumed reduction of the travel time penalty to predict possible changes is not sufficient to capture this complexity. We suggest that approaches that consider individual variations, and all the factors that we have identified to have an influence on activity-travel patterns would be more accurate in estimating possible travel behavior changes. This would also allow to realistically depict the variations in usage of AVs, from skeptics who would only drive in an autonomous vehicle without making any modifications to how much more they travel, or how far they travel, to the enthusiasts who would remodel their daily schedules.

Considering the highly contextual nature of this research, and its limitations in terms of sample size and profiles, its objective was not to provide direct policy recommendation, but rather provide a quantitative basis to motivate the need for different approaches to assessing travel behavior impact of autonomous vehicles. Thus, we can only recommend to explore modeling approaches that can include the influence of the drivers of activity and travel changes as identified, as well as the inter-dependencies between the various schedule changes.

6.3 REFLECTION ON RESEARCH

We have discussed our findings and their implications in the context of this experiment in the results chapters (chapters 4 and 5) and in this chapter. In this section, we choose to reflect on this research with respect to existing literature, as well as its limitations.

6.3.1 Reflection

As has been discussed, literature exploring specific activity-travel changes, considering the different interactions between activities, is limited, but recent papers have tried to study them in depth. We will compare our findings to the expectations of a focus group conducted by Pudāne, Rataj, Molin, *et al.*[64], as well as those of a similar recent paper by Kim, Mokhtarian, and Circella[31].

Pudāne, Rataj, Molin, *et al.*'s research objectives are similar to ours, as they explored changes in the daily activities of future AV-users using qualitative focus group data [64]. Though, these effects were not identified quantitatively as our study did, some results were similar. Pudāne, Rataj, Molin, *et al.* found that on-board activities and stationary activities influence each other, and identified other influential factors like time pressure and activity facilitation and flexibility. While our research identified some consistency in respondents' expectation of changes in travel distance and frequency, most do not expect to travel further or more often, and very few have reported to make changes to the number of trips, the authors found more variation in the respondents' expectations. Their conclusions were consistent with ours, in that the travel time penalty approach to predicting travel behavior changes over-estimates these changes, and cannot capture the variety of potential impacts, and thus, must be rethought [64].

Similarly, Kim, Mokhtarian, and Circella also studied the changes travelers expect to make in a hypothetical all-AV era, identifying clusters of changes [31]. While we used data in which respondents reported their full daily schedules, Kim, Mokhtarian, and Circella designed a list of potential changes to activity schedules, which include inter-dependencies with other changes, and asked respondents the likelihood of experiencing such changes [31]. As such, the addition of our research was extracting these inter-dependencies from the schedules. The paper also identified that older, lower income individuals would be less inclined to expect activity changes, while younger and more technology oriented people would make use of the *hands-free* travel. In contrast, they found that the respondent's expectations of potential changes in their time (traveling earlier/later, eating/working in the car and freeing up time later...) were the lowest. Though the umbrella of *time flexibility* included different layers of changes that we explored individually in this research, we have found more significant expected changes here. Overall, though, they agree that travel behavior changes driven by autonomous vehicles may be more modest than expected, which was also supported by other studies ([69], [49]).

6.3.2 Limitations

Evidently, this research is subject to limitations on different levels. Below, we discuss the most significant limitations in terms of data and research and analysis choices.

The limitations of the survey data and methods were discussed in chapter 3, but we can expand on these limitations with respect to the research and analysis process. As the survey data includes commuters only, inherent biases in the sample are to be expected. Indeed, as we exclude non-commuters, our findings regarding the impacts of autonomous vehicles on travel patterns do not encompass the full range of possible travel, such as long distance trips. Additionally, as the schedules were self-reported, we must consider that there may be errors and inaccuracies in the daily activity-travel schedules. Other responses, like time pressure, are subject to the interpretation of the respondents. By using these variables as bases for comparisons, there was an inherent assumption that all respondents evaluate them similarly, which may not be completely true. Finally, it is important to remember that this survey was collected in the Netherlands, so our findings, especially as they relate to time use choices, must be interpreted considering the geographical and cultural context this entails. Furthermore, choices made in the data preparation stage influenced our analysis. One of the most important choices was eliminating observations based on a set of criteria (see chapter 3, section 3.2) that we generated based on the goals of this research. Because our study focused on commuters, eliminating responses with no work activities and inconsistent travel was consistent with our goals. Nonetheless, these responses could have been addressed as potential scenarios of individuals expecting a complete overhaul of their schedules.

In terms of methods, the choice to use latent class analysis limited the analysis possibilities and the schedule change metrics we could explore. Furthermore, the choice to use a clustering method aggregates the observations, and does provides limited insights on the observations that may not fit any of the profiles, or that fit all the profiles. Further exploration of these specific responses could have been valuable in understanding the characteristics and preferences of those respondents.

As for some analysis choices, some assumptions were made to accommodate for special cases of schedules. One of them relates to the cases in which all trips were eliminated in the AV schedule. Throughout our analysis, we assumed that the trips occurred at the same time they did in order to avoid extreme outliers skewing the departure time differences to extremes. It must be pointed out that the choice to use activity duration differences as a metric for activity changes in the schedules was based on the observed significance of these indicators, but they do not give more insights on the changes in number of activities or their order. Other indicators could have been used to complement the activity duration changes, like activity fragments, or the start times of activities. Further, it would have been a strong addition to the analysis to study "bundles" of activities separated by the main trips i.e pre-work and post-work. Though the discussion in the results section addressed and speculated on the dynamics of interactions between the trips and the adjacent activities, a complete analysis in which said activities were clearly distinguished could have complemented our analysis.

6.4 RECOMMENDATIONS FOR FUTURE RESEARCH

This research has provided some understanding of how daily travel-activity schedules may be changed in the era of autonomous vehicles, but more work could be done to expand on these findings.

As discussed, the survey data had several limitations, in its inherent assumptions, but also in its access and sample. Therefore, a first recommendation would be to include location and geographical characteristics as potential forces influencing the travel behavior expectations. Additionally, as this research could only address commuter travel, future research can explore possible changes in long distance travel in the era of autonomous vehicles, especially as many studies have identified it as a potential source of additional travel demand [64][31]. Furthermore, though we identified some associations between income levels and schedule changes, the lack of representation of several income groups (minimum income, 2x the average income and >2x the average income) made income statistically insignificant. As such, we recommend further studies to cover these ranges to have a clearer view of the Dutch population. Further, in line with introducing more nuance to the analysis, another recommendation would be to add other possible autonomous vehicle modes beyond privately owned vehicles. Indeed, not only have we observed high reluctance to purchasing autonomous vehicles, but travelers also had no options other than private autonomous vehicles in the survey, which limits their travel choices. As such, we recommend conducting similar studies with more travel mode options, traditional non-vehicle ones, but also shared autonomous vehicles and autonomous taxis, to get a clearer representation of possible scenarios of future vehicle automation.

Considering the autonomous vehicles technology remains in progress, perception and acceptance may be dynamic, as knowledge and exposure increases over time. For that, we recommend research to address and evaluate how the expected impacts evolve over time, especially once the technology becomes available. In the meantime, chauffeur experiments that simulate the experience of having an autonomous vehicles, similar to that in [25], can provide additional insights on travel behavior without relying on self-reporting, which could often be flawed . Individuals are often irrational in decision making, and their biases often inadvertently interfere, as they often base decisions on heuristics. Thus, observational research will allow to reduce the impact of self-reporting biases.

Seeing as this research, along with others, has put to question the accuracy and value of travel time penalty approaches as a predictor of travel behavior changes, we recommend more empirical research and modeling studies to further explore the value of traveling in an autonomous vehicle. This value would include the different perceived benefits of AVs (the ability to engage in activities on-board, the additional comfort, the reduced stress etc.), all while considering the individuals' characteristics, needs and preferences, as well as constraints. Comparing findings from such models with traditional travel time penalty approaches would be informative.

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A SURVEY QUESTIONS AND ANSWER KEY

This appendix contains an overview of the survey questions and answer key.

Table 22: Socio-economic attributes

Question	**Answer**	**Key**
Gender	1	Man
	2	Woman
Age Group	1	18-24
	2	25-34
	3	35-44
	4	45-54
	5	55-64
	6	65-74
	7	75+
Highest Education Completed	1	No education \Elementary education
	2	LBO \VBO \VMBO \MBO 1
	3	MAVO \First 3 years of HAVO and VWO \VMBO
	4	MBO 2, 3, 4 of MBO (Old structure)
	5	HAVO and VWO (Bovenbouw) \HBO-\WO-Foundation
	6	HBO-\WO-Bachelor
	7	HBO-\WO-Master or Doctoral
	8	Do not know \do not want to tell
Family Size	0 - 8	Number of family members
Children	0 - 3	Number of children
Family Cycle	1	Single; up to and including 34 y.o.
	2	Single; 35 - 39 y.o.
	3	Single; 40 - 49 y.o.
	4	Singe; 50 - 64 y.o.
	5	Single; 65+ y.o.
	6	Adult household; main breadwinner up to and including 34 y.o.
	7	Adult household; main breadwinner 35 - 39 y.o.
	8	Adult household; main breadwinner 40 - 49 y.o.
	9	Adult household; main breadwinner 50 - 64 y.o.
	10	Adult household; main breadwinner 65+ y.o.
	11	Household with children; youngest up to and including 12 y.o.
	12	Household with children; youngest 13 - 17 y.o.
Income Group	1	Minimum (<€ 14.100 Euro)
	2	Below average (€ 14.100 - <€ 29.500)
	3	Average (€ 29.500 - <€ 43.500), including negative income
	5	1-2x Average (€ 43.500 - <€ 73.000)
	6	2x Average (€ 73.000 - <€ 87.100)
	7	More than 2x average (>= € 87.100)
	9	Do not know \do not want to tell
Work Type	1	Entrepreneur
	2	Employed (Paid)
	3	Employed by government
	4	Not fit for work
	5	Unemployed \job-searching \assistant

6	Retired
7	Student \pupil (15+)
8	Housewife \househusband \other (incl. <15 y.o.)
9	Do not know \do not want to tell

Table 23: Travel Preferences

Question	Answer	Key
How many days per week do you travel to work?	0	4 or more days a week
	1	1-3 days a week
	2	Almost never, I work from home
What is your main transport mode on a normal working day?	0	Car (as a driver)
	1	Car (as a passenger)
	2	Public transport
	3	Bicycle
	4	Walk
How long does a single trip take to your work-/ study location (door to door)?	0	<10 min
	1	10 - 30 min
	2	30 - 60 min
	3	>60 min
Think of the last workday where you (primarily) used travel mode for all your trips. Which day of the week was that?	0	Monday
	1	Tuesday
	2	Wednesday
	3	Thursday
	4	Friday
	5	Saturday
	6	Sunday
What time did you wake up on that day?		Time

Table 24: AV-related Questions

Question	Answer	Key
Do you own a car?	0	Yes
	1	No
How long do you travel daily on average? (Trips to all activities, including walking time.)		Time
Imagine that you have access to an AV in addition to your current transport modes. Do you think you would overall travel further or more often?	0	Yes, I would travel further away or more often
	1	No, I would travel just as far and often as I do now
	2	No, I would travel nearer or less often
	3	I don't know
If you had access to an AV, how often would you use it for your daily trips, if the travel costs were comparable with your current travel costs?	0	For (almost) all of my trips
	1	For many of my trips
	2	For some of my trips
	3	For (almost) none of my trips
	4	I don't know
Do you suffer from motion sickness during travel? (When you make use of a car, bus, train, bicycle, plane or a boat)	0	Yes, almost or always almost
	1	Yes, often
	2	Yes, sometimes
	3	No, never of almost never
Motion sickness explanation		Open-ended answer
Do you often try out new technology before your friends and neighbors?	0	Often or very often
	1	Sometimes
	2	Seldom or (almost) never
Have you heard of automated vehicles prior to this survey?	0	Yes
	1	Maybe
	2	No
If you need a new car, would you then consider obtaining an AV, in case it costs just as much as a normal car and you do not need driving license?	0	Yes
	1	Maybe
	2	No
	3	I don't think I will ever buy a car
Considering AV Explanation		Open ended answer
Assess the daily time pressure that you experience - do you have a feeling that you have too little time for all the things that you must do in a day?	0	Very low time pressure
	1	Low time pressure
	2	Not low, not high time pressure
	3	High time pressure
	4	Very high time pressure
If you had two extra hours per day, what would you use them for?		Open ended answer
Could you perform your work tasks in a comfortable car where you do not get motion sick and have internet connection?	0	Yes, all or almost all of my work tasks
	1	Most of my work tasks
	2	Some of my work tasks
	3	No, none or almost none of my work tasks

B DESCRIPTIVE STATISTICS

The characteristics, socio-economic and travel, of the sample at hand were discussed in chapter 3, and this appendix contains summaries of the frequencies of responses.

	Data (N = 495)
Age Group	
18-24	42 (8)
25-34	107 (22)
35-44	103 (21)
45-54	152 (31)
55-64	90 (18)
65-74	1 (0)
75+	0 (0)
Education	
No education, Elementary education	13 (3)
LBO, VBO, VMBO, MBO 1	22 (4)
MAVO, First 3 years of HAVO and VWO,VMBO	27 (5)
MBO 2, 3, 4 of MBO (Old structure)	142 (29)
HAVO and VWO (Bovenbouw),HBO,WO Foundation	42 (8)
HBO, WO Bachelor	148 (30)
HBO, WO Master or Doctoral	101 (20)
Do not know, do not want to tell	0 (0)
Family Size	
0	0 (0)
1	42 (8)
2	107 (22)
3	103 (21)
4	152 (31)
5	90 (18)
6	1 (0)
7	0 (0)
8	0 (0)
Children	
No children	251 (51)
One child	83 (17)
2 Children	118 (24)
3 chldren or more	43 (9)

Family Cycle	
Single; up to and including 34 y.o.	31 (6)
Single; 35 to 39 y.o.	13 (3)
Single; 40 to 49 y.o.	17 (3)
Single; 50 to 64 y.o.	29 (6)
Single; 65+ y.o.	1 (0)
Adult household; main breadwinner up to and including 34 y.o.	49 (10)
Adult household; main breadwinner 35 - 39 y.o.	13 (3)
Adult household; main breadwinner 40 - 49 y.o.	36 (7)
Adult household; main breadwinner 50 - 64 y.o.	135 (27)
Adult household; main breadwinner 65+ y.o.	12 (2)
>Household with children; youngest up to and including 12 y.o.	110 (22)
Household with children; youngest 13 - 17 y.o.	49 (10)
Income Group	
Minimum (< € 14.100 Euro)	0 (0)
Below average (€ 14.100 - < € 29.500)	249 (50)
Average (€ 29.500 - < € 43.500), including negative income	197 (40)
1-2x Average (€ 43.500 - < € 73.000)	49 (10)
2x Average (€ 73.000 - < € 87.100)	0 (0)
More than 2x average (>= € 87.100)	0 (0)
Do not know, do not want to tell	0 (0)
Work Type	
Entrepreneur	27 (5)
Salaried Employee	363 (73)
Employed by government	61 (12)
Not fit for work	0 (0)
Unemployed, job-searching, assistant	0 (0)
Retired	0 (0)
Student, pupil (15+)	44 (9)
Housewife, househusband, other(incl. < 15 y.o.)	0 (0)
Do not know, do not want to tell	0 (0)

Figure 17: Frequencies of Individual Characteristics (percentages in parentheses)

	Data (N = 495)
Travel Frequency	
4 or more days a week	384 (78)
1-3 days a week	111 (22)
(Almost) never, I work from home	0 (0)
Travel Mode	
Car (as a driver)	322 (65)
Car (as a passenger)	4 (1)
Public transport	72 (15)
Bicycle	95 (19)
Walk	2 (0)
Travel Time	
< 10 min	0 (0)
10 - 30 min	249 (50)
30 - 60 min	197 (40)
>60 min	49 (10)
Car Ownership	
Yes	424 (86)
No	71 (14)
Average Daily Travel Time (minutes)	
min	10
median	70
max	210
mean (sd)	79.96 ± 43.10

Figure 18: Frequencies of Travel Characteristics

	Data (N = 495)
Travel Behavior Change	
Yes, I would travel further away or more often	73 (15)
No, I would travel just as far and often as I do now	375 (76)
No, I would travel nearer or less often	2 (0)
I don't know	45 (9)
Frequency of AV	
For (almost) all of my trips	204 (41)
For many of my trips	77 (16)
For some of my trips	85 (17)
For (almost) none of my trips	75 (15)
I don't know	54 (11)
Motion Sickness	
Yes, almost or always almost	2 (0)
Yes, often	15 (3)
Yes, sometimes	77 (16)
No, never of almost never	401 (81)
Technology Adoption Speed	
Often or very often	115 (23)
Sometimes	219 (44)
Seldom or (almost) never	161 (33)
Knowledge of Autonomous Vehicles	
Yes	467 (94)
Maybe	6 (1)
No	22 (4)
Consider Driving Autonomous Vehicles	
Yes	155 (31)
Maybe	186 (38)
No	136 (27)
I don't think I will ever buy a car	18 (4)
Daily Time Pressure	
Very low time pressure	13 (3)
Low time pressure	70 (14)
Not low, not high time pressure	240 (48)
High time pressure	156 (32)
Very high time pressure	16 (3)
Work Possible in the Car	
Yes, all or almost all of my work tasks	57 (12)
Most of my work tasks	100 (20)
Some of my work tasks	172 (35)
No, none or almost none of my worktasks	166 (34)
Facilitation Level	
Ideal facilitation	239 (48)
Partial Facilitation	256 (52)

Figure 19: Frequencies of AV-related Characteristics

C LOGISTIC REGRESSION MODELS

C.1 ON-BOARD ACTIVITY CHANGE REGRESSION MODEL

Model with Hard Indicators

		Estimate	Std error	Z-value	p-value	Odds-ratio
Intercept		-1.25	1.24	-1.01	0.32	0.29
Gender	Woman*	0.22	0.21	1.07	0.29	1.25
Age Group	25-34	0.53	0.57	0.93	0.35	1.70
	35-44	0.11	0.61	0.19	0.85	1.12
	45-54	-0.22	0.60	-0.38	0.71	0.80
	55-64	0.00	0.62	0.00	1.00	1.00
	65-74	14.20	535.40	0.03	0.98	1468864.19
Work Type	Employed (Private)	0.62	0.46	1.35	0.18	1.86
	Employed (Government)	0.73	0.52	1.41	0.16	2.08
	Student	0.86	0.70	1.22	0.22	2.35
Children	1	-0.18	0.30	-0.62	0.53	0.83
	2	0.06	0.26	0.21	0.83	1.06
	3+	0.57	0.37	1.54	0.13	1.78
Education	LBO VBO VMBO MBO	-0.08	0.90	-0.09	0.93	0.92
	MAVO year 3 HAVO and VWO VMBO	0.38	0.82	0.46	0.64	1.46
	MBO 2, 3, 4 or old MBO	0.76	0.76	1.00	0.32	2.14
	HAVO and VWO HBO WO propaedeutic year	0.91	0.77	1.17	0.24	2.48
	HBO/ WO Bachelor	1.24	0.75	1.65	0.10	3.45
	Master/PhD*	1.75	0.77	2.27	0.02	5.73
Income Group	Below average	-0.72	0.82	-0.87	0.38	0.49
	Average	-1.41	0.78	-1.80	0.07	0.25
	1-2x Average	-1.14	0.76	-1.49	0.14	0.32
	2x Average	-1.46	0.81	-1.79	0.07	0.23
	More than 2x average	-0.84	0.78	-1.08	0.28	0.43

Model with Hard and Soft Indicators

Onboard		Estimate	Std error	Z-value	p-value	Odds-ratio
Intercept		0.00	1.28	0.00	1.00	1.00
Gender	Woman*	0.44	0.22	2.03	0.04	1.55
Education	LBO VBO VMBO MBO	0.66	0.91	0.73	0.47	1.94
	MAVO year 3 HAVO and VWO VMBO	0.71	0.85	0.84	0.40	2.04
	MBO 2, 3, 4 or old MBO	0.79	0.73	1.08	0.28	2.19
	HAVO and VWO HBO WO propaedeutic year	1.21	0.78	1.55	0.12	3.35
	HBO/ WO Bachelor	1.16	0.72	1.60	0.11	3.19
	Master/PhD*	1.49	0.73	2.03	0.04	4.44
Income Group	Below average	-0.91	0.87	-1.05	0.29	0.40
	Average*	-1.70	0.83	-2.06	0.04	0.18
	1-2x Average	-1.45	0.81	-1.80	0.07	0.23
	2x Average*	-1.68	0.85	-1.97	0.05	0.19
	More than 2x average	-1.33	0.82	-1.62	0.11	0.26
Travel Time	30-60 minutes**	0.66	0.22	3.02	0.00	1.93
	>60 minutes**	1.06	0.36	2.98	0.00	2.89
Daily Time Pressure	Low	-0.91	0.68	-1.33	0.18	0.40
	Not low, not high	-0.29	0.63	-0.46	0.64	0.75
	High	0.12	0.64	0.18	0.86	1.12
	Very High	-0.34	0.83	-0.41	0.68	0.71
Is Work Possible in the Car	Most tasks	-0.16	0.36	-0.43	0.67	0.86
	Some tasks	-0.35	0.33	-1.06	0.29	0.70
	No task*	-0.82	0.36	-2.31	0.02	0.44
Motion Sickness	Yes, often	0.62	1.74	0.36	0.72	1.86
	Yes, sometimes	0.34	1.66	0.21	0.84	1.41
	No, never or almost never	0.21	1.65	0.13	0.90	1.24

C.2 STATIONARY ACTIVITY CHANGE REGRESSION MODEL

Model with Hard Indicators

Stationary Activity Change		Estimate	Std error	Z-value	p-value	Odds-ratio
Intercept		-1.77	1.20	-1.48	0.14	0.17
Gender	Woman	0.10	0.21	0.49	0.62	1.11
Age Group	25-34	0.85	0.58	1.47	0.14	2.34
	35-44	0.36	0.61	0.59	0.55	1.44
	45-54	0.39	0.60	0.64	0.52	1.47
	55-64	0.30	0.63	0.47	0.64	1.34
	65-74	14.61	535.41	0.03	0.98	2212514.04
Work Type	Employed (Private)	0.37	0.47	0.79	0.43	1.44
	Employed (Government)	0.77	0.52	1.47	0.14	2.15
	Student	0.73	0.70	1.04	0.30	2.08
Children	1	-0.04	0.29	-0.15	0.88	0.96
	2	0.13	0.26	0.48	0.63	1.13
	3+	0.65	0.37	1.77	0.08	1.92
Education	LBO VBO VMBO MBO	0.43	0.86	0.50	0.62	1.54
	MAVO year 3 HAVO and VWO VMBO	0.38	0.82	0.46	0.64	1.46
	MBO 2, 3, 4 or old MBO	0.54	0.76	0.71	0.48	1.71
	HAVO and VWO HBO WO Foundation	0.37	0.78	0.48	0.63	1.45
	HBO/ WO Bachelor	0.85	0.75	1.14	0.26	2.34
	Master/PhD	1.05	0.76	1.37	0.17	2.84
Income Group	Below average	-0.46	0.76	-0.61	0.54	0.63
	Average	-0.92	0.71	-1.29	0.20	0.40
	1-2x Average	-0.61	0.69	-0.88	0.38	0.54
	2x Average	-0.60	0.74	-0.80	0.42	0.55
	More than 2x average	-0.28	0.71	-0.40	0.69	0.76

Model with Hard and Soft Indicators

Stationary Activity Change		Estimate	Std error	Z-value	p-value	Odds-ratio
Intercept *		-0.45	0.68	-0.66	0.51	0.64
Gender	Woman	0.19	0.22	0.85	0.39	1.20
Travel Time	30-60 minutes*	0.52	0.21	2.41	0.02	1.67
	>60 minutes*	0.77	0.34	2.26	0.02	2.15
New Technology Adoption Speed	Sometimes	0.01	0.26	0.04	0.97	1.01
	Seldom or (almost) never*	0.54	0.29	1.86	0.06	1.72
Daily Time Pressure	Low	-0.89	0.67	-1.34	0.18	0.41
	Not low, not high	-0.44	0.62	-0.71	0.48	0.64
	High	-0.03	0.63	-0.06	0.96	0.97
	Very High	-0.54	0.81	-0.67	0.51	0.58
Is Work Possible in the Car	Most tasks	0.05	0.35	0.14	0.89	1.05
	Some tasks	-0.25	0.32	-0.76	0.45	0.78
	No task**	-0.98	0.35	-2.78	0.01	0.38

C.3 TRAVEL CHANGE REGRESSION MODEL

Model with Hard Indicators

Travel Change		Estimate	Std error	Z-value	p-value	Odds-ratio
Intercept		1.29	1.26	1.03	0.31	3.65
Gender	Woman*	0.51	0.23	2.26	0.02	1.67
Age Group	25-34	-0.47	0.62	-0.76	0.45	0.62
	35-44	-0.40	0.65	-0.62	0.54	0.67
	45-54	-0.81	0.64	-1.27	0.21	0.45
	55-64	-0.48	0.67	-0.72	0.47	0.62
	65-74	-13.24	535.41	-0.03	0.98	0.00
Work Type	Employed (Private)	-0.48	0.45	-1.06	0.29	0.62
	Employed (Government)	-0.67	0.53	-1.26	0.21	0.51
	Student	-1.47	0.77	-1.91	0.06	0.23
Children	1	0.46	0.32	1.46	0.14	1.59
	2*	0.56	0.29	1.97	0.05	1.76
	3+	0.04	0.45	0.10	0.92	1.04
Education	LBO VBO VMBO MBO 1	-0.57	0.92	-0.62	0.54	0.57
	MAVO year 3 HAVO and VWO VMBO	-0.02	0.83	-0.03	0.98	0.98
	MBO 2, 3, 4 or old MBO	-0.51	0.78	-0.66	0.51	0.60
	HAVO and VWO HBO WO Foundation	0.01	0.79	0.02	0.99	1.02
	HBO/ WO Bachelor	-0.05	0.76	-0.07	0.95	0.95
	Master/PhD	-0.45	0.79	-0.57	0.57	0.64
Income Group	Below average*	-1.90	0.81	-2.35	0.02	0.15
	Average*	-1.64	0.74	-2.23	0.03	0.19
	1-2x Average*	-1.59	0.72	-2.22	0.03	0.20
	2x Average*	-1.60	0.78	-2.07	0.04	0.20
	More than 2x average	-1.36	0.73	-1.86	0.06	0.26

Model with Hard and Soft Indicators

Travel Change		Estimate	Std error	Z-value	p-value	Odds-ratio
Intercept		1.34	1.41	0.95	0.34	3.82
Gender	Woman	0.42	0.24	1.73	0.08	1.53
Education	LBO VBO VMBO MBO	-0.49	0.94	-0.53	0.60	0.61
	MAVO year 3 HAVO and VWO VMBO	-0.03	0.85	-0.03	0.97	0.97
	MBO 2, 3, 4 or old MBO	-0.67	0.78	-0.86	0.39	0.51
	HAVO and VWO HBO WO Founadtion	-0.15	0.80	-0.19	0.85	0.86
	HBO/ WO Bachelor	-0.36	0.77	-0.47	0.64	0.69
	Master/PhD	-0.76	0.79	-0.96	0.34	0.47
Work Type	Employed (Private)	-0.45	0.45	-1.01	0.31	0.64
	Employed (Government)	-0.64	0.54	-1.18	0.24	0.53
	Student	-0.76	0.79	-0.96	0.34	0.47
Income Group	Below average*	-1.76	0.82	-2.15	0.03	0.17
	Average*	-1.56	0.75	-2.08	0.04	0.21
	1-2x Average*	-1.53	0.70	-2.19	0.03	0.22
	2x Average	-1.48	0.78	-1.89	0.06	0.23
	More than 2x average	-1.20	0.74	-1.62	0.10	0.30
Travel Frequency	1-3 days a week*	0.54	0.26	2.06	0.04	1.72
New Technology Adoption Speed	Sometimes	0.31	0.30	1.04	0.30	1.37
	Seldom or (almost) never	0.14	0.34	0.42	0.68	1.15
Daily Time Pressure	Low	-0.96	0.68	-1.41	0.16	0.38
	Not low, not high	-0.85	0.64	-1.34	0.18	0.43
	High	-0.65	0.66	-0.99	0.32	0.52
	Very High	-0.58	0.89	-0.66	0.51	0.56
Is Work Possible in the Car	Most tasks	0.35	0.41	0.84	0.40	1.42
	Some tasks	0.38	0.39	0.97	0.33	1.46
	No task	-0.04	0.42	-0.11	0.91	0.96

D

LATENT CLASS CLUSTERING MODELS- NO COVARIATES

On-board Activity Duration Change Model

Starting with the single activity duration change, a model with the 4 most common on-board activity duration change indicators is made. The optimal model was a 4-cluster model, as shown in Table 25. Through this model, it is observed that while no-change is most common, clear patterns in on-board activities change emerge. Of these, we recognize a distinction between travelers who engage in a single activity during travel, mostly work or spare-time, while others engage in all activities somewhat equally, with one activity being slightly more prevalent, again work or spare-time.

As expected, the majority of respondents experience little change in the duration of activities during travel, and are part of cluster 1 (72.12% of the sample). But as we move to clusters with more significant on-board changes, preferences in the activities most common during travel emerge. The next two clusters represent travelers who engage in strictly one activity over the others during travel. Cluster 2 (10.36% of the sample) represents the work-focused individuals, who report a considerable increase in the duration of spare time during travel, with a slight increase in spare-time as well. The latter is more pronounced in cluster 3(10.18% of the sample), though the work duration decreases, leaving meal time on-board to increase. Considering the high significance of increases in spare time and work on-board individually in these clusters, we hypothesize that the large changes in these two indicators often occur independently, and that there is little association between them. Of course, this is also associated with limitations of travel duration, as it would difficult to observe large increases in both work and spare time if the total travel time is not increased too, which in this experiment is highly limited.

However, we observe that engaging in activities on-board does not necessarily entail a single activity focus, as cluster 4 (7.35% of the sample) represents the travelers who engage in all four activities considerably, with getting ready, spare time, and meals being relatively equal in distribution. We can hypothesize that this portion of the sample is one that could engage in multiple activities in one trip, for instance in the morning trip getting ready and eating breakfast. These travelers can also engage in different activities at different trips. For instance, they could engage in work activities in the work-bound trip, but use the home-bound trip for relaxing and spare time.

Table 25: Latent Class Profiles of the 4-class Solution with On-board Activity Duration Change Indicators

		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Indicators- Duration Change	Cluster Size (%)	72.12%	10.36%	10.18%	7.35%
Getting Ready On-board	Mean	0.000	0.000	0.000	0.149
Work On-board	Mean	0.000	0.572	-0.001	0.260
Meal On-board	Mean	0.000	0.000	0.150	0.138
Spare Time On-board	Mean	0.000	0.123	0.549	0.131

Stationary Activity Duration Change Model

Moving on to the stationary activity duration change, a 4 cluster model was found to be optimal, as shown in Table 26. A clear observation to be made is that the durations of work and eating outside travel are reduced in all clusters, while spare time and sleep generally increase. This indicates that the latter two activities are not sufficient as they are in the original schedules for most travelers. As such, work and meals are likely to be directly transferred to the travel episodes, while there seems to be an underlying demand for sleep and spare time, which could lead to increases in these activities even if some are transferred to the travel episodes.

Similarly to the on-board activities, the first and most populated cluster (65% of the sample) is one with minimal changes. That is, it represents the portion of sample that experiences the least changes in duration of activities outside travel. This is essentially the reference cluster with hardly any modifications to activity duration.

Cluster 2 (12.28% of the sample) represents the spare-time seeking travelers, whose working hours outside travel are reduced, and possibly replaced by spare time activities. The reduction of working hours is possibly a result of transferring work activities to the travel episode, as well as modifications to travel departure time, which provide free time to be allocated to spare time. While less significant, time spent getting ready and eating is also reduced, which we hypothesize is associated with the increase in the duration of sleep, and the transfer of getting ready and eating activities to the travel episode. This dynamic is mostly apparent in morning pre-work activities, as longer sleep duration leaves less time in the morning for getting ready and eating breakfast, and maintaining the same durations would require delayed travel. Similar patterns are observed in the remaining clusters, though in cluster 3 (11.38% of the sample), stationary meals decrease in duration moreso than work, while sleep increases more than spare time. Cluster 4 (11.33% of the sample) also represents travelers who experience similar changes, but less dramatically than in other clusters. Indeed, sleep and spare-time increase in duration, but much less comparatively, while time spent getting ready increases. As such, it is expected that these changes could be associated with delays in morning trips, as the longer sleep duration would reduce the time available for the regular morning activities. As one of these (getting ready) is increased as well, we hypothesize that work-bound travel would be delayed.

Table 26: Latent Class Profiles of the 5-class Solution with Stationary Activity Duration Change Indicators

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Indicators- Duration Change	Cluster Size (%)	65.00%	12.28%	11.38%	11.33%	
Sleep Stationary	Mean	0.000	0.088	0.088	0.051	
Getting Ready Stationary	Mean	0.000	-0.082	-0.001	0.027	
Work Stationary	Mean	0.000	-0.211	-0.044	-0.015	
Meal Stationary	Mean	0.000	-0.009	-0.072	-0.094	
Spare Time Stationary	Mean	0.000	0.329	0.053	0.003	

E

LATENT CLASS CLUSTERING MODELS- COVARIATES

On-board and Stationary Activities Duration Change

			Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
	Indicators- Duration Change	**Cluster Size (%)**	55.91%	15.97%	11.99%	10.42%	5.71%
	Getting Ready On-board	Mean	0.000	0.000	0.027	0.023	0.094
	Work On-board	Mean	0.000	0.000	0.258	0.178	0.503
	Meal On-board	Mean	0.000	0.000	0.211	0.000	0.000
	Spare Time On-board	Mean	0.000	0.000	0.212	0.503	0.006
	Sleep Stationary	Mean	0.000	0.039	0.130	-0.001	0.086
	Getting Ready Stationary	Mean	0.000	0.024	-0.039	0.001	-0.109
	Work Stationary	Mean	0.000	0.063	-0.096	0.003	-0.555
	Meal Stationary	Mean	0.000	-0.012	-0.149	-0.001	-0.002
	Spare Time Stationary	Mean	0.000	0.029	0.156	0.010	0.395
	Covariates						
Activity Facilitation	Ideal	Mean	0.482	0.480	0.559	0.394	0.536
	Partial	Mean	0.518	0.520	0.441	0.606	0.464
Gender	Man	Mean	0.667	0.646	0.475	0.530	0.679
	Woman	Mean	0.333	0.354	0.525	0.471	0.321
Age_group	18-24	Mean	0.098	0.064	0.068	0.098	0.036
	25-34	Mean	0.156	0.279	0.271	0.332	0.321
	35-44	Mean	0.199	0.176	0.237	0.217	0.2501
	45-54	Mean	0.337	0.291	0.288	0.236	0.2499
	55-64	Mean	0.210	0.177	0.136	0.118	0.1429
	65-74	Mean	0.000	0.013	0.000	0.000	0
Education	No education \Elementary education	Mean	0.036	0.013	0.017	0.000	0.036
	LBO \VBO \VMBO \MBO 1	Mean	0.058	0.064	0.017	0.000	0
	MAVO \up to year 3 HAVO and VWO \VMBO	Mean	0.069	0.051	0.017	0.059	0
	MBO 2, 3, 4 of MBO old structure	Mean	0.330	0.380	0.085	0.217	0.1429
	HAVO en VWO bovenbouw \HBO-\WO	Mean	0.087	0.089	0.034	0.137	0.0357
	HBO-\WO-bachelor	Mean	0.275	0.254	0.390	0.293	0.5

	HBO-\WO-master or doctoral	Mean	0.145	0.151	0.441	0.295	0.2857
Children	0 children	Mean	0.489	0.594	0.525	0.552	0.357
	1 child	Mean	0.188	0.114	0.153	0.117	0.214
	2 children	Mean	0.246	0.203	0.220	0.273	0.2145
	3+ children	Mean	0.076	0.089	0.102	0.059	0.2143
Income Group	Minimum (<€14.100)	Mean	0.007	0.038	0.017	0.059	0.036
	Below average (€14.100 - <€29.500)	Mean	0.073	0.075	0.102	0.080	0.071
	Average (€29.500 - <€43.500), including negative income	Mean	0.199	0.152	0.153	0.176	0.1428
	1-2x Average (€43.500 - <€73.000)	Mean	0.413	0.417	0.220	0.354	0.3216
	2x Average (€73.000 - <€87.100)	Mean	0.109	0.115	0.085	0.097	0.107
	More than 2x average (>= €87.100)	Mean	0.199	0.203	0.424	0.235	0.3215
Work Type	Entrepreneur	Mean	0.054	0.064	0.034	0.059	0.071
	Employed (Private)	Mean	0.743	0.758	0.695	0.669	0.75
	Employed by government	Mean	0.116	0.090	0.170	0.136	0.1786
	Student \pupil (15+)	Mean	0.087	0.089	0.102	0.137	0
Travel Frequency	4 or more days a week	Mean	0.790	0.772	0.661	0.785	0.893
	1-3 days a week	Mean	0.210	0.228	0.339	0.215	0.1072
Travel Mode	Car (as a driver)	Mean	0.616	0.634	0.695	0.744	0.750
	Car (as a passenger)	Mean	0.015	0.000	0.000	0.000	0
	Public transport	Mean	0.141	0.153	0.153	0.136	0.1785
	Bicycle	Mean	0.221	0.213	0.153	0.121	0.0715
	Walk	Mean	0.007	0.000	0.000	0.000	0
Daily Time Pressure	Very low time pressure	Mean	0.025	0.038	0.017	0.039	0.000
	Low time pressure	Mean	0.178	0.151	0.017	0.139	0.0357
	Not low, not high time pressure	Mean	0.522	0.506	0.339	0.471	0.3929
	High time pressure	Mean	0.250	0.292	0.559	0.293	0.5357
	Very high time pressure	Mean	0.025	0.013	0.068	0.059	0.0358
Is Work Possible In Car	Yes, all or almost all of my work tasks	Mean	0.083	0.101	0.085	0.236	0.321
	Most of my work tasks	Mean	0.163	0.153	0.390	0.214	0.3216
	Some of my work tasks	Mean	0.323	0.417	0.407	0.354	0.2499
	No, none or almost none of my worktasks	Mean	0.431	0.329	0.119	0.197	0.1071
Motion Sickness	Yes, almost or always almost	Mean	0.004	0.000	0.000	0.020	0.000
	Yes, often	Mean	0.018	0.062	0.034	0.042	0.0357
	Yes, sometimes	Mean	0.123	0.177	0.220	0.196	0.2144
	No, never of almost never	Mean	0.855	0.761	0.746	0.743	0.7499

New Technology Adaption Speed	Often or very often	Mean	0.232	0.203	0.254	0.176	0.357
	Sometimes	Mean	0.449	0.430	0.390	0.510	0.3929
	Seldom or (almost) never	Mean	0.319	0.367	0.356	0.314	0.2499
Self Driving Car Knowledge	Yes	Mean	0.928	0.949	1.000	0.981	0.893
	Maybe	Mean	0.018	0.000	0.000	0.000	0.0357
	No	Mean	0.054	0.051	0.000	0.020	0.0714
Travel Time (Inactive)	10 - 30 min	Mean	0.598	0.506	0.288	0.335	0.321
	30 - 60 min	Mean	0.330	0.418	0.525	0.509	0.5359
	>60 min	Mean	0.073	0.076	0.186	0.156	0.1429
Travel Time Behaviour Change Key (Inactive)	Travel further and more often	Mean	0.116	0.140	0.271	0.156	0.179
	Travel just as far and often as now	Mean	0.779	0.747	0.661	0.765	0.7859
	Travel nearer and less often	Mean	0.004	0.013	0.000	0.000	0
	I don't know	Mean	0.101	0.101	0.068	0.079	0.0356
Expected AV Usage Frequency (Inactive)	For (almost) all of my trips	Mean	0.341	0.393	0.509	0.528	0.750
	For many of my trips	Mean	0.134	0.178	0.237	0.156	0.143
	For some of my trips	Mean	0.188	0.177	0.153	0.177	0.0358
	For (almost) none of my trips	Mean	0.203	0.114	0.068	0.079	0.0712
	I don't know	Mean	0.134	0.139	0.034	0.060	0.0001
Considers Self Driving Car (Inactive)	Yes	Mean	0.236	0.329	0.441	0.353	0.678
	Maybe	Mean	0.380	0.418	0.356	0.411	0.2144
	No	Mean	0.344	0.190	0.203	0.216	0.0716
	I don't think I will ever buy a car	Mean	0.040	0.064	0.000	0.020	0.0357

On-board, Stationary Activities and Travel Departure Time Change

			Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
	Indicators	**Cluster Size (%)**	44.22%	18.57%	17.58%	11.05%	8.58%
	Getting Ready On-board	Mean	0.000	0.000	0.000	0.000	0.128
	Work On-board	Mean	0.000	0.184	0.000	0.274	0.166
	Meal On-board	Mean	0.000	0.000	0.000	0.185	0.059
	Spare Time On-board	Mean	0.000	0.000	0.251	0.089	0.262
	Sleep Stationary	Mean	0.000	0.054	0.000	0.097	0.066
	Getting Ready Stationary	Mean	0.000	0.033	0.000	0.016	-0.159
	Work Stationary	Mean	0.000	-0.047	-0.001	-0.137	-0.114
	Meal Stationary	Mean	0.000	0.006	-0.001	-0.131	-0.074
	Spare Time Stationary	Mean	0.000	0.100	0.006	0.139	0.138
	Work Trip Departure	Mean	0.000	0.001	0.024	0.074	0.007
	Home Trip Departure	Mean	0.001	0.000	-0.121	-0.062	0.004
	Covariates						
Activity Facilitation	Ideal	Mean	0.512	0.527	0.395	0.504	0.447
	Partial	Mean	0.488	0.473	0.605	0.496	0.5529
Gender	Man	Mean	0.696	0.681	0.570	0.490	0.417
	Woman	Mean	0.304	0.319	0.430	0.510	0.5832
Age Group	18-24	Mean	0.088	0.055	0.116	0.037	0.119
	25-34	Mean	0.175	0.329	0.128	0.256	0.3382
	35-44	Mean	0.180	0.165	0.267	0.196	0.2959
	45-54	Mean	0.350	0.264	0.280	0.351	0.2145
	55-64	Mean	0.208	0.176	0.209	0.160	0.0321
	65-74	Mean	0.000	0.011	0.000	0.000	0
Education	No education \Elementary education	Mean	0.032	0.022	0.023	0.000	0.024
	LBO \VBO \VMBO \MBO 1	Mean	0.060	0.055	0.035	0.000	0.0238
	MAVO \up to year 3 HAVO and VWO \VMBO	Mean	0.065	0.044	0.081	0.000	0.0477
	MBO 2, 3, 4 of MBO old structure	Mean	0.327	0.341	0.302	0.055	0.2148
	HAVO and VWO (Bovenbouw) \HBO-\WO-Foundation	Mean	0.083	0.088	0.128	0.055	0.0239
	HBO-\WO-bachelor	Mean	0.272	0.242	0.338	0.422	0.3621
	HBO-\WO-master or doctoral	Mean	0.161	0.209	0.093	0.467	0.304
Children	0 children	Mean	0.521	0.560	0.488	0.443	0.454
	1 child	Mean	0.184	0.121	0.163	0.187	0.1642
	2 children	Mean	0.226	0.220	0.280	0.330	0.1234
	3+ children	Mean	0.069	0.099	0.070	0.040	0.2582

Income Group	Minimum (<€14.100)	Mean	0.000	0.033	0.058	0.019	0.024
	Below average (€14.100 - <€29.500)	Mean	0.078	0.055	0.058	0.087	0.1499
	Average (€29.500 - <€43.500), including negative income	Mean	0.208	0.121	0.186	0.145	0.2178
	1-2x Average (€43.500 - <€73.000)	Mean	0.392	0.450	0.453	0.127	0.3129
	2x Average (€73.000 - <€87.100)	Mean	0.119	0.110	0.082	0.094	0.0932
	More than 2x average (>= €87.100)	Mean	0.203	0.231	0.163	0.527	0.2023
Work Type	Entrepreneur	Mean	0.055	0.022	0.035	0.139	0.059
	Employed (Private)	Mean	0.752	0.747	0.732	0.643	0.7212
	Employed by government	Mean	0.110	0.143	0.141	0.142	0.103
	Student \pupil (15+)	Mean	0.083	0.088	0.093	0.076	0.117
Travel Frequency	4 or more days a week	Mean	0.839	0.813	0.698	0.636	0.730
	1-3 days a week	Mean	0.161	0.187	0.302	0.364	0.2696
Travel Mode	Car (as a driver)	Mean	0.613	0.660	0.673	0.651	0.759
	Car (as a passenger)	Mean	0.018	0.000	0.000	0.000	0
	Public transport	Mean	0.133	0.143	0.152	0.201	0.1458
	Bicycle	Mean	0.231	0.198	0.163	0.148	0.0957
	Walk	Mean	0.005	0.000	0.012	0.000	0
Daily Time Pressure	Very low time pressure	Mean	0.018	0.022	0.046	0.037	0.024
	Low time pressure	Mean	0.180	0.121	0.175	0.039	0.0685
	Not low, not high time pressure	Mean	0.539	0.462	0.489	0.419	0.3186
	High time pressure	Mean	0.240	0.363	0.255	0.454	0.5359
	Very high time pressure	Mean	0.023	0.033	0.035	0.051	0.0531
Is Work Possible In Car	Yes, all or almost all of my work tasks	Mean	0.083	0.143	0.093	0.106	0.292
	Most of my work tasks	Mean	0.161	0.220	0.199	0.344	0.2248
	Some of my work tasks	Mean	0.323	0.341	0.348	0.469	0.3255
	No, none or almost none of my worktasks	Mean	0.433	0.297	0.360	0.082	0.1573
Motion Sickness	Yes, almost or always almost	Mean	0.000	0.000	0.012	0.019	0.000
	Yes, often	Mean	0.028	0.044	0.012	0.037	0.0477
	Yes, sometimes	Mean	0.101	0.209	0.174	0.201	0.2414
	No, never of almost never	Mean	0.871	0.748	0.802	0.743	0.7109
New Technology Adaption Speed	Often or very often	Mean	0.254	0.242	0.163	0.272	0.174
	Sometimes	Mean	0.461	0.440	0.477	0.423	0.3132
	Seldom or (almost) never	Mean	0.286	0.319	0.360	0.305	0.5132
Self Driving Car Knowledge	Yes	Mean	0.926	0.934	0.942	0.982	1.000
	Maybe	Mean	0.023	0.000	0.000	0.019	0
	No	Mean	0.051	0.066	0.058	0.000	0

Travel Time (Inactive)	10 - 30 min	Mean	0.595	0.451	0.511	0.357	0.303
	30 - 60 min	Mean	0.336	0.428	0.431	0.492	0.4619
	>60 min	Mean	0.069	0.121	0.058	0.150	0.2355
Travel Time Behaviour Change Key (Inactive)	Travel further and more often	Mean	0.120	0.143	0.116	0.190	0.280
	Travel just as far and often as now	Mean	0.756	0.769	0.814	0.737	0.6717
	Travel nearer and less often	Mean	0.005	0.011	0.000	0.000	0
	I don't know	Mean	0.120	0.077	0.070	0.074	0.0483
Expected AV Usage Frequency (Inactive)	For (almost) all of my trips	Mean	0.350	0.495	0.383	0.398	0.632
	For many of my trips	Mean	0.148	0.165	0.105	0.241	0.1895
	For some of my trips	Mean	0.193	0.143	0.175	0.164	0.1232
	For (almost) none of my trips	Mean	0.171	0.088	0.233	0.160	0.0319
	I don't know	Mean	0.138	0.110	0.105	0.037	0.024
Considers Self Driving Car (Inactive)	Yes	Mean	0.244	0.385	0.267	0.434	0.442
	Maybe	Mean	0.368	0.385	0.454	0.335	0.3311
	No	Mean	0.355	0.176	0.233	0.213	0.2031
	I don't think I will ever buy a car	Mean	0.032	0.055	0.046	0.019	0.0239