MASTER

The impact of automated driving on travel demand

a study into the factors that determine if and how private shared automated vehicles will influence individuals' transportation mode choice, trip frequency and average trip length

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Master Thesis

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by

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Thesis Information

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Best regards,
Rutger Klein

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List of concepts and abbreviations

Active transportation modes
Un-motorized transportation modes that require physical exercise, such as walking and bicycling.

ADAS
Advanced Driver Assistance Systems, which are included in vehicles to support the driving process. Examples are navigation systems, (adaptive) cruise control and automated driving systems.

Autonomous taxi
Completely self-driving taxi, which does not need a chauffeur and can theoretically drive unmanned to / from client locations.

AV
Automated Vehicle. A vehicle that can sense (part of) their surroundings and use that information to take over some, or all, driving tasks from the human driver

ITS
Intelligent Transportation Systems. Advanced applications that use real-time traffic-related information to optimize traffic management or to advice / warn travelers.

Level of automation
Index made by SAE International used to categorize AVs based on their technical capabilities. A higher level of automation refers to a higher degree of autonomy of the AV and less aspects of the driving task that need to be executed by the human driver.

PT
Public Transportation. All motorized, publicly accessible and shared transportation modes such as buses, trains and subways.

TOD
Transit Oriented Development. A philosophy in spatial planning that emphasizes high density and mixed land use and supports multi-modal travel.

Travel demand
The amount an individual or population intents to travel as a result of activity-travel related decisions. In this report, three aspects of travel demand are considered: Modal shares, travel frequency and average trip length.

VHT
Vehicle Hours Traveled. A value which represents an aggregated amount of hours travelled per car on a certain transportation network over a certain period of time.

VKT
Vehicle Kilometers Traveled. A value which represents an aggregated amount of kilometers travelled per car on a certain transportation network over a certain period of time.

VTT
Value of Travel Time. A value which represents the disutility per minute of travelling with a certain transportation mode. Used in transportation models to represent the utility of different transportation modes.

Summary

Reliable transportation is becoming increasingly difficulty to facilitate, because of growing travel demand, road safety issues and parking scarcity. Because of a lack of space and resources, there is a need for innovative solutions to this problem. Automated driving is such an innovation. It's an umbrella term for technologies that enable vehicles to collect information about their surroundings, and use that information to operate themselves. There are two main types of automated driving technology: Sensor-based and connectivity-based. Sensor-based technologies 'sense' their surroundings by transmitting and receiving signals, while connectivity based technologies use communications between vehicles, infrastructure and other entities as a source of information. Automated vehicles (AV) can be categorized by their 'level of automation'. This index refers to the degree to which the vehicle can drive autonomously and take over driving tasks from the human driver. Level 5 AVs, the highest level, can drive autonomously under any circumstances, enabling them to drive unmanned. This feature makes these vehicles suitable for automated (unmanned) parking and driverless taxis.

Due to their technical capabilities, AVs have the opportunity to deal with a lot of transportation-related issues. For instance, they are expected to reduce the chance of an accident while traveling by up to 90%. Furthermore, they can drive very close to each other due to their precise movement control and instant reflexes, reducing drag and improving road capacity. Finally, if autonomous taxis would take over the place of privately owned vehicles, automated driving could reduce parking demand considerably. Other opportunities of AVs for society are to improve the mobility of non-drivers, reduce impact on the environment, stimulate high-tech, automotive and transportation sectors, reduce the variable costs of mobility and improve the potential for multi-modal travel.

However, automated driving also harbors a number of threats. The technology is prone to hacking, abuse, bugs and misinterpretation of entities in the surroundings of AVs. Furthermore, it could lead to urban sprawl, decreasing usage of active transportation modes and a massive loss of jobs in the transportation sector. Besides, there are a lot of uncertainties regarding liability in case of an accident caused by the AV, and the confidentiality/security of personal data obtained by AVs.

Governments, AV developers and consumers are concerned with these opportunities and threats. Each of these stakeholders is a crucial factor in the success of automated driving. Governments must create the conditions that AV developers can use to create a value proposition that appeals to the consumer. In order to pursue effective policies, governments need to increase their knowledge about the impacts of automated driving.

One of the most uncertain impacts of automated driving is on the transportation system. This is because there are many arguments why automated driving would decrease and increase the demand for infrastructure. On the one hand, there are 'operational' impacts of AVs on the transportation system, such as the effects of shorter headways, unmanned travel, smooth ac-/deceleration and fewer traffic accidents. On the other hand, there are 'behavioral' impacts of AVs on the transportation system, such as the effects of changes in transportation mode choice, travel frequency, destination choice, home- and work location, departure time and the satisfaction of latent travel demand of non-drivers.

Particularly the behavioral impacts of automated driving are very underexposed in the literature. Several travel demand models from recent literature suggest that automated driving could have a considerable impact on modal shares and vehicle kilometers traveled. However, the parameters and procedures used to represent the impact of automated driving on travel demand are based on assumptions and very generalizing. There is a lack of, and need for, statistically supported knowledge about the impact of automated driving on travel demand, and the personal and contextual factors that influence this relationship.

This research tries to fill this gap with a stated choice experiment about the impacts of automated driving on travel demand. This experiment is part of a questionnaire used to collect data from respondents. In the questionnaire, respondents are first required to state their traveling context in terms of destinations visited and corresponding travel characteristics. The destinations pertain to on one of two trip motives: Work/education or non-grocery shopping. After this section, they are required to pretend to have access to an AV, after which they have the opportunity to add new destinations they would visit. Then, they must state if and how they would change their choices for transportation mode and travel frequency for each destination. Respondents are presented with three such choice tasks, each of which contains the description of a single AV based on 4 attributes: Type, safety, travel time and travel costs. The response variables for transportation mode choice and travel frequency were used to calculate the impact of automated driving on modal shares, travel frequency and weighted average trip length. Several ordinal regression models were then estimated to identify which personal and contextual factors are related to these impacts.

The sample used is 749 Dutch inhabitants aged 18 years and older, that roughly represent the characteristics of the Dutch population in terms of gender, age groups, household size and car ownership. Both drivers and non-drivers were featured in the sample. The sample has a relatively high share of highly educated individuals. 216 of the responses have been acquired by asking friends and acquaintances, while 533 of the responses have been acquired by involving a market panel which was paid for by the Netherlands Institute for Transport Policy Analysis (KiM).

The results of this study indicate an increase of 20-25% in total vehicle hours traveled per car for both work/education and non-grocery shopping travel, regardless of whether the AV presented is privately owned by the respondent or shared as an autonomous taxi. The increase in car usage goes at the cost of public transportation and active transportation mode usage, which are declining by respectively 40-55% and 15-30%. Approximately 80% of the work/education destinations and 70% of the non-grocery shopping destinations are not visited more or less frequently after gaining access to an AV. The rest of the destinations, both those pertaining to work/education and non-grocery shopping activities, are visited more frequently just as often as less frequently. For approximately 65% of the respondents, average length of non-grocery shopping trips does not change after gaining access to an AV. 23% would increase average trip length for non-grocery shopping trips.

Of all the AV attributes, ‘private ownership’ and ‘75% less chance on accidents than regular cars’ are most positively related to changes in travel demand, while the attributes ‘autonomous taxi’, ‘15% slower than regular cars’ and ‘15% more expensive than regular cars’ are related to comparatively less changes in travel demand. Several socio-demographic- and contextual factors are related to the extent of changes in transportation mode choice, travel frequency and/or average trip length. These are: Sex, age, car ownership, education level, household size, type of living area, currently used transportation modes, shopping center type and proximity of destination.

The conclusion is that automated driving can drastically increase car usage for work/education and non-grocery shopping travel, but will only have a small to moderate effect on travel frequency and average trip length. In order to deal with the extra car traffic, authorities could use dedicated AV-lanes, stimulate multi-modal travel with autonomous taxis and/or legally limit the amount of unmanned kilometers traveled by AVs and autonomous taxis. Further research could focus on long-term behavioral impacts such as work-/ home location and car ownership choices and the impact of automated driving on land value and urban structure.

1. Introduction

“We want transportation to be as reliable as running water”, said Travis Kalanick, co-founder of Uber and nominated person of the year 2015 by TIME magazine (Foroohar, 2015). Although talking about the goals of his company at the time, this quote seems to apply to all of society. Transportation is becoming more and more important in a globalizing world with an ever increasing demand for mobility. However, reliable transportation in the future cannot be taken for granted, because there are numerous threats around the corner.

For starters, travel time duration and stability are under pressure. According to the US Office of Highway Policy Information (2017), the total Vehicle Kilometers Traveled (VKT) on US roads is estimated to increase by on average 1.07% per year from 2015 to 2035. This amounts to a total VKT increase of approximately 24% over 20 years. In the Netherlands, road VKT also shows an increasing trend after several years of stagnation (Centraal Bureau voor de Statistiek, 2016). These developments can be seen in figure 1.1. The main problem caused by increasing traffic intensity is road congestion. Congestion leads to travel time delays, fuel waste, air pollution, increased chance on accidents, vehicle depreciation, unstable travel times and traveler frustration. From 2015 to 2021, travel time loss in the Netherlands is expected to further increase by 38%. The effects will predominantly be noticeable on the highways (Ministry of Infrastructure and the Environment, 2016). Frequent peak-time, long-distance car travelers, such as daily commuters, are therefore facing serious mobility issues in the near future. Other transportation modes such as mass transit are often no valid alternatives, because they aren’t flexible enough to provide travel time improvements (Dutch, 2015). Road congestion does not only impact car travelers, it affects all of society. Calculations from the Dutch research institute TNO estimate that travel time delays have caused 1.1 billion euros of damages to the Dutch economy in 2015 (Nederlandse Publieke Omroep, 2016).

Secondly, road safety is threatened. Although the total amount of fatal traffic accidents in the Netherlands has been on a decline for more than a decade, the substantial increase of traffic fatalities in 2015 is cause for concern. Besides, the amount of serious traffic-related injuries in the Netherlands has been increasing steadily over the past 10 years (Weijermars, Van Schagen, Goldenbeld, Bos, & Stipdonk, 2016). Recent developments in the amount of traffic accidents can be

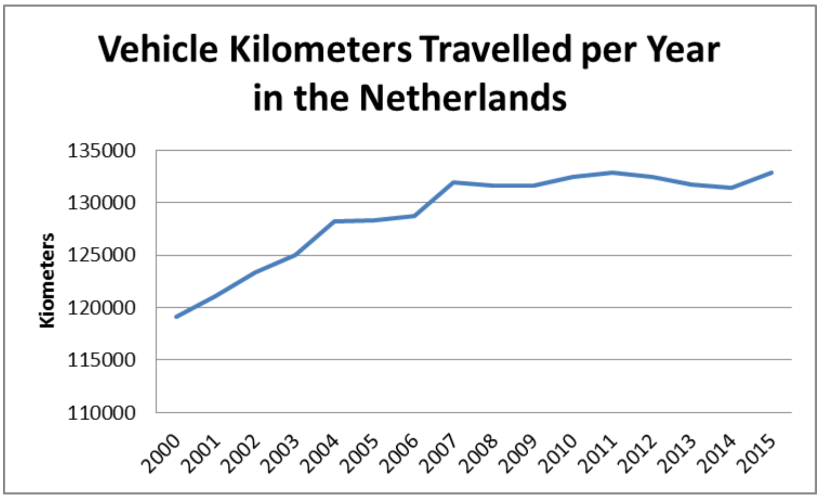
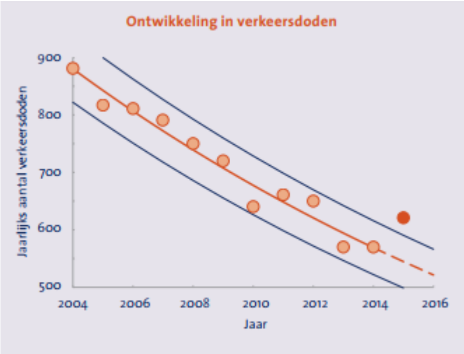
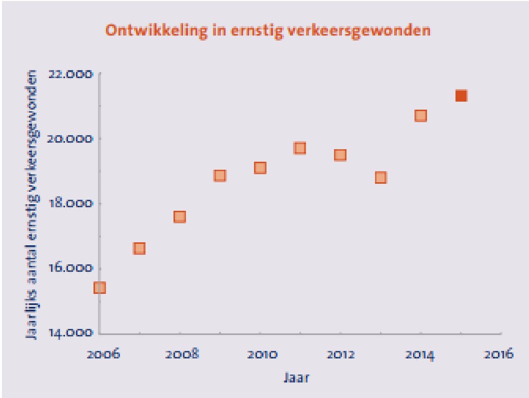


Figure 1.1: Developments of VKT in the Netherlands. Source: Centraal Bureau voor de Statistiek, 2016



Afbeelding 1: Aantal verkeersdoden in 2015 (donkeroranje cirkel) ten opzichte van de aantallen in 2004-2014 (lichtoranje cirkels). De oranje doorgetrokken lijn toont de trend in de periode 2004-2014, met daarvan de prognose (stippellijn) en het 95%-betrouwbaarheidsinterval (blauwe lijnen).

Figure 1.2: Developments in number of fatal traffic accidents in the Netherlands. Source: Weijermars et al., 2016



Afbeelding 2: Aantal ernstig verkeergewonden in 2015 (donkeroranje symbool) en de aantallen in 2006-2014 (lichtoranje symbolen).

Figure 1.3: Developments in number of serious traffic-related injuries in the Netherlands. Source: Weijermars et al., 2016

seen in figure 1.2 and 1.3. 39% of traffic fatalities are car drivers. People aged 60 plus and people aged 20-29 are relatively often the victim in traffic accidents: respectively 47% and 14% (Weijermars et al., 2016). Similarly to the travel time delays, the impacts of traffic accidents are not confined to those directly affected. The Dutch National Institute for Traffic Safety Research (SWOV) estimated that in 2015, traffic accidents have resulted in 13 to 15.4 billion euros of damages to the Dutch economy, which equals approximately 2% of the gross domestic product of that year (Stichting Wetenschappelijk Onderzoek Verkeersveiligheid, 2017).

Thirdly, car parking is becoming an increasingly problematic aspect of traveling. Car ownership has been increasing steadily in the Netherlands, by approximately 25% between 2000 and 2015 (Centraal Bureau voor de Statistiek, 2015). Meanwhile cars are only being used for approximately 5% of the time (Barter, 2013). This means that for 95% of the time, they are parked. This causes high parking demand and is also very costs-inefficient, because the costs of owning a vehicle consist for more than half of fixed costs at this usage rate (Nationaal Instituut voor Budgetvoorlichting, n.d.). The increasing parking demand leads to scarcity, higher parking rates, longer and more unstable travel times, not to mention an additional source of frustration for car travelers. The addition of parking spots along the streets lead to deterioration of the public area, while parking garages take up valuable land in city centers and are often an unattractive sight as well (Summer, 2012).

All these issues considered, it can be concluded that infrastructure planners are facing major challenges in their goal to facilitate reliable transportation in the future. Simply developing more infrastructure to support the increasing travel- and parking demand is not a durable solution and is often infeasible because of limited space and funding. As with any problem dealing with finite resources, the key to a sustainable solution is to reduce demand and look for alternative sources or instead. One such solution is Transit-Oriented Development (TOD) of urban areas. The main principles of TOD are to create a fine mixture of land uses, increase urban density and link private- and public transportation modes together, in order to minimize local travel demand and maximize mass-transit output (Transit Oriented Development Institute, n.d.). However, not all areas are suitable for TOD. An innovative solution that requires less space and resources are Intelligent Transportation Systems (ITS). ITS use real-time data obtained by sensors embedded in the infrastructure to manage and regulate traffic and warn / advice travelers. This improves road safety, traffic flow and parking convenience.

Another innovative solution is automated driving. ‘Automated Vehicles’ (AVs) can monitor their driving environment and use that information to take over driving tasks from the human driver. The ‘level of automation’ of an AV represents the extent to which the vehicle can drive autonomously. It can range from limited applications such as adaptive cruise control (level 1), to full autonomy under any circumstances (level 5). Automated driving systems generally supersede human drivers in operating the vehicle because they can process more information and are not inconsistent like humans. This results in many benefits of AVs over regular vehicles. For instance, some AVs can drive very close to their predecessor, reducing drag and fuel usage and potentially increasing highway capacity up to 273% (Tientrakool, Ho, & Maxemchuk, 2011). The amount of traffic accidents should decrease considerably as well with automated driving, since approximately 90% of traffic accidents are caused by human errors (Fagnant & Kockelman, 2015). In the Netherlands, approximately 18% of traffic jams are caused by accidents (Kleinjan, 2017), so AVs could substantially improve travel time stability on highways and main roads by reducing the number of traffic accidents. Furthermore, level 5 AVs are able to travel unmanned. This feature could be the solution for parking problems and inefficient vehicle usage, because it allows vehicles to drive to and from peripheral parking locations autonomously, or decrease car ownership because car sharing becomes much more convenient.

Automated driving is clearly a technology with high potential to improve person mobility. However currently, only low-level AVs are legally allowed on public roads for private usage (Eugensson & Brännström, 2013). This is because authorities need time to evaluate the opportunities and threats of automated driving, before changing their legislation. This causes the need for more knowledge about the impacts of automated driving on society.

One of the most uncertain impacts of automated driving is on the transportation system (Litman, 2015). As mentioned previously, the reduced number of accidents and more efficient usage of the available infrastructure could potentially improve traffic flow considerably. However, unmanned kilometers made by AVs and autonomous taxis could increase VKT by up to 75% (Schoettle & Sivak, 2015). Furthermore, automated driving could lead to a considerable change in travel demand (Fagnant & Kockelman, 2015; Gruel & Stanford, 2016). For instance, there is a large amount of latent travel demand from non-drivers such as elderly, youth, physically restrained people etc. If AVs will become accessible to these people, it could lead to an increase of 11% in total VKT (Sivak & Schoettle, 2015). Furthermore, automated driving is expected to increase the utility of traveling by car, because it offers travel convenience and the ability to spend time traveling effectively (Gruel & Stanford, 2016). This could lead to a considerable increases in the modal share of cars (Childress, Nichols, Charlton, & Coe, 2014), total travel frequency (Childress et al., 2014; Gruel & Stanford, 2016; Pendyala & Bhat, 2014) and average trip length (Gucwa, 2014).

Several researchers have attempted to simulate the impacts of high utility AVs on a transportation system. The results from these studies indicate increases in VKT of up to 32% (Correia & van Arem, 2016) that can be attributed to the improved travel experience of AVs over regular cars. However, the parameters and procedures used to represent the impact of automated driving on travel demand are based on assumptions and very generalizing. There is a lack of, and need for, statistically supported knowledge about the impact of automated driving on travel demand, and the personal and contextual factors that influence this relationship (Gruel & Stanford, 2016). This study aims to fill this research gap by trying to find statistical evidence for changes in travel demand due to the availability of AVs or autonomous taxis, and to identify the relevant factors. This translates into the following main research question:

Main question: *What is the impact of automated driving on travel demand and which factors influence this relationship?*

The concepts used in this study to represent travel demand are: Transportation mode choice, travel frequency and average trip length. Several sub-questions are used in this study to refine the research problem and add structure to the research:

Sub-question 1: *What are the technical capabilities of automated vehicles?*

Sub-question 2: *What is the potential impact of automated driving on society?*

Sub-question 3: *Who are the main stakeholder involved in automated driving?*

Sub-question 4: *What is the potential impact of automated driving on the transportation system?*

Sub-question 5: *How can the impact of automated driving on travel demand be analyzed?*

The research approach will be a stated choice experiment. The data collection tool will be an online questionnaire in which respondents must indicate changes in their travel demand while pretending they could use an AV or autonomous taxi. These AVs and autonomous taxis have randomly varying attributes level of the attributes: Level of automation, safety, travel time and travel costs. Other factors included in this study are socio-demographic characteristics and the traveling context of the individual. The traveling context is based on a number of destination by trip motive. Only destinations pertaining to work- education or (non-grocery) shopping activities are considered.

The population targeted are inhabitants of the Netherlands over 18 years old. The sample used for the questionnaire is 749 respondents who are partially friends, relatives and acquaintances (N=216), and partially members from a market panel from online fieldwork specialist PanelClix (N=533). Because the results from the 'convenience sample' (N=216) were collected first, participants from the panel were selected in such a way that age and sex statistics of the complete sample would represent the Dutch population. The involvement of the market panel was paid for by the Netherlands Institute for Transportation Policy Analysis (KiM).

The results from this study consist of a number of parameters indicating the impact of automated driving and autonomous taxis on modal shares, travel frequency and average trip length for work/education and non-grocery shopping activities, accompanies by a list of relevant factors for each impact.

The main target group of this study are infrastructure planners and researchers. The results of this study give insight into the potential impacts of automated driving on travel demand which can be used for developing transportation policies and improving the accuracy of travel demand models.

This study can also be relevant to AV developers and transportation services. The results provide insight into the willingness to use AVs among different target groups and under different circumstances.

The outline of this thesis will be as follows. First, a literature study has been conducted to present the technical capabilities of AVs, their future impacts on society, an analysis of the stakeholders, some of the latest attempts to simulate the impact of AVs on transportation systems and a review of factors that are likely related to AV usage and changes in travel demand. Secondly, the research approach will be explained from the experiment design to the data collection method and data analysis approach. Thirdly, the results of the research will be presented and finally, the results and research approach will be critically discussed and recommendations will be presented for policy and future research.

2. Literature study

This chapter presents a review of literature on the subject of vehicle automation and their impacts on society and the transportation system. The purpose of this review is to give the reader some important background knowledge into automated driving and to give understanding about the relevancy of this study. Furthermore, conclusions and implications from existing literature are used to formulate hypotheses. These hypotheses are visualized in the form of a conceptual model in the last section of the literature study.

2.1 Technical capabilities

Automated vehicles (AVs) can be described as vehicles that can sense (part of) their surroundings and use that information to take over some, or all, driving tasks of the driver/passenger (SAE International, 2014). The vehicle senses their surroundings by receiving and interpreting signals. The resulting information is used to operate the driving systems accordingly. Signals received by AVs can fall under two categories: They are either reflections of the surroundings captured by sensors (called sensor-based), or dedicated messages sent by other entities such as vehicles, satellites or infrastructure (called connectivity-based). The following sub-sections will evaluate and compare sensor-based and connectivity-based technologies, and discuss how developments in both technologies are important for the future of automated driving.

2.1.1 Sensor-based technology

Sensor-based technologies are developed to make the vehicle aware of their surroundings. There are different types of sensors-based technologies available but in essence, they all work rather similar: A transmitter sends out waves in different directions, the waves reflect of surfaces in the vehicles vicinity, and a sensor captures the reflected waves. The reflections are used to assess the distance, angle, location etc. of a surface. Interpretation software can then be used to identify patterns for recognizing shapes, object motion etc. Cameras are the only sensor type used in sensor-based technologies that do not transmit waves; they only receive reflections (of visible light) that have a different source. Because cameras cannot time the difference between the moment of transmitting and receiving signals, they are less suitable for estimating distance. However, cameras are the only type of sensor that can identify colors and therefore a crucial technology for detecting traffic signage. Table 2.1 summarizes the different types of sensors used for automated driving. Each sensor has their advantages and disadvantages. Because of this, the best results are achieved when multiple technologies are combined to complement each other and to enable cross-referencing (KPMG, 2012).

Table 2.1: Sensor types used in vehicle automation. Sources: Bagloee, Tavana, Asadi, & Oliver, 2016; Bridges, 2015; KPMG, 2012; Santo, 2016

Sensor	Type of waves	Main applications	Limitations	Strong points
SONAR	Ultrasound	Short range object/collision detection	Can only be used for very short range applications such as parking assistance	Cheapest technology
IR-sensor	Infrared	Lane marking detection	Relatively short range	Can detect brightness of surfaces, even in the dark
RADAR	Radiowaves	Locating objects and determining their motion	Mediocre range and accuracy	Functional under any (weather-) circumstances, can use reflections to sense behind objects
LIDAR	Laser light	3D mapping of environment	Very expensive, uses massive amounts of data	360 degree sight, long range, most accurate 3D mapping
Camera	Visible light	Identifying objects such as traffic signs and types of scenery	Uses massive amounts of data, interpretation of images is highly complex	Cheapest sensor, long range, can identify textures and colors

2.1.2 Connectivity-based technology

Connectivity-based technologies are developed to make vehicles ‘communicate’ with their surroundings. For this to work, vehicles and infrastructure must be equipped with transmitters to send information messages about their location, velocity, regulations etc. These message are received by the AV and processed. Intermediate receiver/transmitters such as satellites can be used to facilitate communications. Unfortunately, the leading pinpointing technology used by satellites, GPS, is currently not accurate enough to be used in automated driving technology (KPMG, 2012).

Connectivity-based technologies have several advantages over sensor-based technologies. Firstly, the signals used are much more straightforward and are therefore less complicated to interpret by the AV. Secondly, the technology is much less expensive because it can replace costly sensor equipment. Thirdly, intensive communication between vehicles about their location and route can be used to optimize navigation systems and improve traffic flow considerably (Bagloee et al., 2016). However, in spite of these advantages connectivity-based technology are currently much less common in vehicle automation than sensor-based technologies. This is because connectivity-based technologies can only work efficiently if enough other vehicles and infrastructure are connected (KPMG, 2012). This is a problem because since this technology is rather new, only a fraction of the vehicle fleet is connected. Renowned consultancy company KMPG predicts that connectivity-based technologies are crucial for the success of automated driving (KPMG, 2012). The government can play an important role in making more vehicles ‘connected’, because they can legally force car manufacturers to equip new vehicles with information transmitters, in order to make them detectable by connectivity-based technologies in AVs (Underwood, Marshall, & Niles, 2014).

2.1.3 Advanced driver assistance systems

Currently there are already several applications of sensor-based technology on the market. Such applications are commonly called Advanced Driver Assistance Systems (ADAS). Only ADAS that monitor the driving environment *and* use this information to operate the vehicle are considered 'automation' technologies (SAE International, 2014). Automation technologies may be restricted to certain driving functions, such as those involved in steering (lateral control) or those involved in speed regulation (longitudinal control). Table 2.2 shows a list of currently existing ADAS. Most of these ADAS rely on sensor-based technology, although some could theoretically also be developed with connectivity-based technology. An example of an exclusively connectivity-based application is platooning. In a 'platoon', one or several vehicles follow a leader vehicle. The leader vehicle communicates their movement to the follower-vehicles, which mimic the movements of the leader vehicle closely. This allows for a very small headway between the vehicles (Fagnant & Kockelman, 2015).

Table 2.2: List of advanced driver assistance systems

Type of automation	ADAS
No automated driving	Navigation Cruise control Lane departure warning Blind spot monitor Parking sensor / back-up alert Etc.
Lateral automation (steering)	Lane keeping assistance Lane changing assistance
Longitudinal automation (acceleration)	Adaptive cruise control (ACC) Traffic jam assistance Emergency braking system
Lateral+longitudinal automation	Automatic parking Collision avoidance system Emergency driver assistant Intersection assistant Platooning Autonomous driving

2.1.4 Level of automation

It can be concluded from the previous text that not all ADAS offer the same degree of automation. Therefore, the term 'automated vehicle' or 'self-driving vehicle' can lead to confusion, because their technical capabilities can vary. Most professionals in the field of vehicle automation deal with this ambiguity by referring to the 'level of automation' of the AV. This level is based on an index made by SAE International (2014). The index identifies 5 different levels of automation, with three primary thresholds. The first one is between level 0 and higher, which indicates the transition from non-automated to automated driving. The definition of automated driving is that technology is used to obtain information about the environment and to use that information to operate the vehicle. The next important threshold is between level 2 and 3. Whereas level 1/2 vehicles still require continuous assistance from the driver, level 3 AVs and onwards are able to drive autonomously, thus allowing the driver to avert their attention from the driving task. Level 3 and 4 AVs can only drive autonomously under specific circumstances, such as on highways or other driving environments with limited complexity. The difference is that level 4 AVs are equipped with systems to bring the vehicle to a safe stop if a request to take over by the driver is ignored. This means the final important threshold is between level 4 and 5, because level 5 AVs are the only ones that can completely drive autonomously under any circumstances, allowing the vehicle to travel unmanned. The explanation of the 'level of automation'-index as formulated by the Society of Automotive Engineers can be seen in figure 2.1.

2.1.5 Car sharing

The ability of level 5 AVs to drive unmanned is a game-changer for the shared vehicle market (Alessandrini, Campagna, Delle Site, Filippi, & Persia, 2015). Current examples of car-sharing concepts are shared ownership and taxis. Shared vehicle concepts are in principle financially very attractive , since the fixed costs of vehicle ownership can be divided between multiple people. On average, the fixed cost of owning a vehicle, including taxes, depreciation, insurance and maintenance , amount to more than half of the total costs of car ownership (Nationaal Instituut voor Budgetvoorlichting, n.d.). The ability of AVs to drive autonomously from one client to the next, called 'trip rebalancing' (Gruel & Stanford, 2016), increases convenience and flexibility of shared ownership, and eliminates the need for chauffeurs in taxi's. Therefore, these services could become much cheaper. The estimated cost price of managing a fleet of autonomous taxis may cost €0,22-€0,26 per driven kilometer, which means autonomous taxis can be offered for almost the same price as privately vehicle usage (Bagloee et al., 2016).

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	**High Automation**	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	**Full Automation**	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 2.1: Level of automation index. Source: SAE International, 2014

2.2 Impact on society

Autonomous driving has many opportunities and threats that will affect society. Some impacts are expected to manifest themselves from the start of automated driving, others will only become evident with advanced forms and applications of automated driving, such as level 5 automated driving or autonomous taxi's. The following sub-sections discuss the potential effects of automated driving on society. Chapter 2.2 ends with a summary of the impacts of automated driving on society.

2.2.1 Safety and security

As mentioned in the introduction, one of the main advantages of automated driving is that it can drastically reduce the amount of traffic accidents. Approximately 90% of traffic accidents are caused by human errors, of which 40% due to alcohol usage, drug usage, distraction or fatigue (Fagnant & Kockelman, 2015). All of these causes can theoretically be solved by transferring driving tasks to an AV. This leads to the assumption that AVs will be involved in at least 50% less crashes than regular cars (Fagnant & Kockelman, 2015). However, there are also still a lot of concerns regarding the integrity of AV technology. A big issue is that computers can still not be interpret images from cameras the way a human driver can (Underwood et al., 2014). This is particularly hard to program, because there are practically infinity situations that can occur while driving that require specific interpretation knowledge. For example, an AV must know the difference between a plastic bag and a cat crossing the street and that it must break after a ball bounces across the street from behind a car. A potential solution for this issue could be to install self-learning programs that analyzes patterns and adapt their own interpretation protocols. However, the problem with self-learning software is that the exact changes they make to their own protocols are out of the developers' control and therefore safety cannot be guaranteed.

Furthermore, there are safety risks involved with connectivity-based technologies. Any machine or device connected to a wireless network is susceptible to hacking. Attempts at hacking AVs have actually proven successful in the past (Muoio, 2016).

Next, public safety can be seriously threatened by the potential of AVs to be used for acts crime or terrorism (Harris, 2014). It is easily understood how an unmanned, remotely controlled and regular looking vehicles are suitable for transporting an explosive into a crowded area. To prevent this from happening, authorities could keep track of AV ownership and usage, but this could be considered an infringement of privacy. The lack of privacy is considered one of the top 5 distressing features of AVs by consumers (Howard & Dai, 2014), because AVs collect a lot of data and there are concerns about personal information being misused, for instance for commercial purposes or in court cases (Fagnant & Kockelman, 2015).

Another issue regarding road safety is that before the entire vehicle fleet can be automated, there must be a long transition period when there are both AVs and non-AVs on the road (Netherlands Institute for Transport Policy Analysis, 2017). This can lead to dangerous situations if the vehicles/drivers are not aware of the other vehicles' capacities (Pendyala & Bhat, 2014). For example, a short headway would require an AV to break rather abruptly to avoid collision, which can cause a collision if the next vehicle is not automated. Also, vehicle platoons blocking highway exits and regular vehicles getting stuck in platoons could lead are potential hazardous situations.

If accidents happen, the next issue is the question of liability. It is currently not defined by the law whether the developer or owner should be liable for damages caused by an AV. Liability regulations will play a big role in the consumer acceptance of AVs, and therefore the success of automated driving. (Bansal, Singh, & Kockelman, 2015; Howard & Dai, 2014; Kyriakidis, Happee, & De Winter, 2015; Schoettle & Sivak, 2014).

2.2.2 Traffic flow

The operational accuracy of automated driving not only improves road safety, but can also benefit traffic flow. For example, vehicles can be programmed to drive more smoothly to reduce the effects of 'shock waves' in traffic (Fagnant & Kockelman, 2015). Furthermore, the number of traffic jams caused by accidents should be reduced, and road capacity could be improved by enabling smaller headway gaps between vehicles (Pendyala & Bhat, 2014). In a later stage when all vehicles are automated, driving lanes could be made narrower as well (Litman, 2015).

However, there are also many reasons to assume that AVs will actually have a negative effect on traffic flow. Firstly, the amount of vehicle kilometers travelled (VKT) could increase substantially because of unmanned travel to/from parking areas and between clients of autonomous taxi's (Boston Consulting Group, 2016; Correia & van Arem, 2016; Fagnant & Kockelman, 2014). Secondly, a virtual driving test shown by Jorrit Kuipers at the 2017 Automotive Week in Helmond showed that the caution with which an AV must drive in urbanized areas to avoid collisions, will cause the vehicle to drive very slowly (Kuipers, 2017). Thirdly, AVs could satisfy the latent travel demand of a large group of non-drivers (Sivak & Schoettle, 2015) and finally, the improved utility of AVs over regular vehicles could cause an increase in overall car travel (Childress et al., 2014; Gucwa, 2014; Kröger, Kuhnimhof, & Trommer, 2016). Due to the contradicting positive and negative impacts of AVs on traffic flow, it remains uncertain whether they will improve or worsen travel time duration and stability.

2.2.3 Spatial planning

Transportation related innovations have a history of influencing the shape and structure of cities. When cars first became available to the public, people realized they could live further away from crowded neighborhoods as they were no longer dependent on public transportation or active transportation modes to travel to their jobs. This has led to a phenomenon called 'urban sprawl', the rapid expansion of cities with sub-urban, low-density and single-function neighborhoods (Alessandrini et al., 2015). Urban sprawl causes a high car dependency, leading to more congestion, traffic accidents and health problems.

Autonomous vehicles are expected to induce more urban sprawl, because travelling, even in traffic jams, is much more attractive if you can be productive or take a nap (Elpern-Waxman, 2016; Underwood et al., 2014)(Underwood et al., 2014). This could once again result in the tendency to move to sub-urban locations where the housing is cheaper and life is more quiet. However, if designed accordingly to Transit Oriented Development (TOD) principles, urban expansion due to automated driving does not have to increase road congestion. Alessandrini et al. (2015) describe how AVs can be used to create the city of the future. This scenario is based on a hierarchy of public transportation (PT) modes, of which the 'lowest' level is the shared AV or automated taxi. Instead of traveling from sub-urban homes to central destination per car, shared AVs could be used as a quick and personal transfer from home to public transportation (PT) hubs. From these hubs, travelers access a network of interconnected PT modes, after which they can use automated taxis again to travel from the final PT hub to their destination, without having to bother about parking the car. This scenario would only work if a significant part of the population is willing to give up private car ownership in favor of vehicle sharing. Figure 2.2 shows a graphical image of the city of the future as perceived by Alessandri et al.

If indeed the inhabitants of city centers and to a lesser extent, (inner) sub-urbs, would choose car sharing over car ownership in the future, this would free up a substantial amount of parking space. Fagnant and Kockelman (2015) state that a single autoAlnomous taxi could replace up to 10 privately owned vehicles and Schoettle & Sivak (2015) state that car sharing could decrease vehicle ownership by 43%. This is a chance for urban planners to improve the attractiveness of the public area, by replacing unnecessary parking area with scenery, trees, parks, public facilities etcetera. Parking spots situated parallel to the roads could also be replaced with biking infrastructure to stimulate the usage of active transportation modes. The demand for large automated taxi depots near transportation hubs could be satisfied rather efficiently, since garages dedicated to AVs could be designed much more compact because they are not accessed by humans regularly.

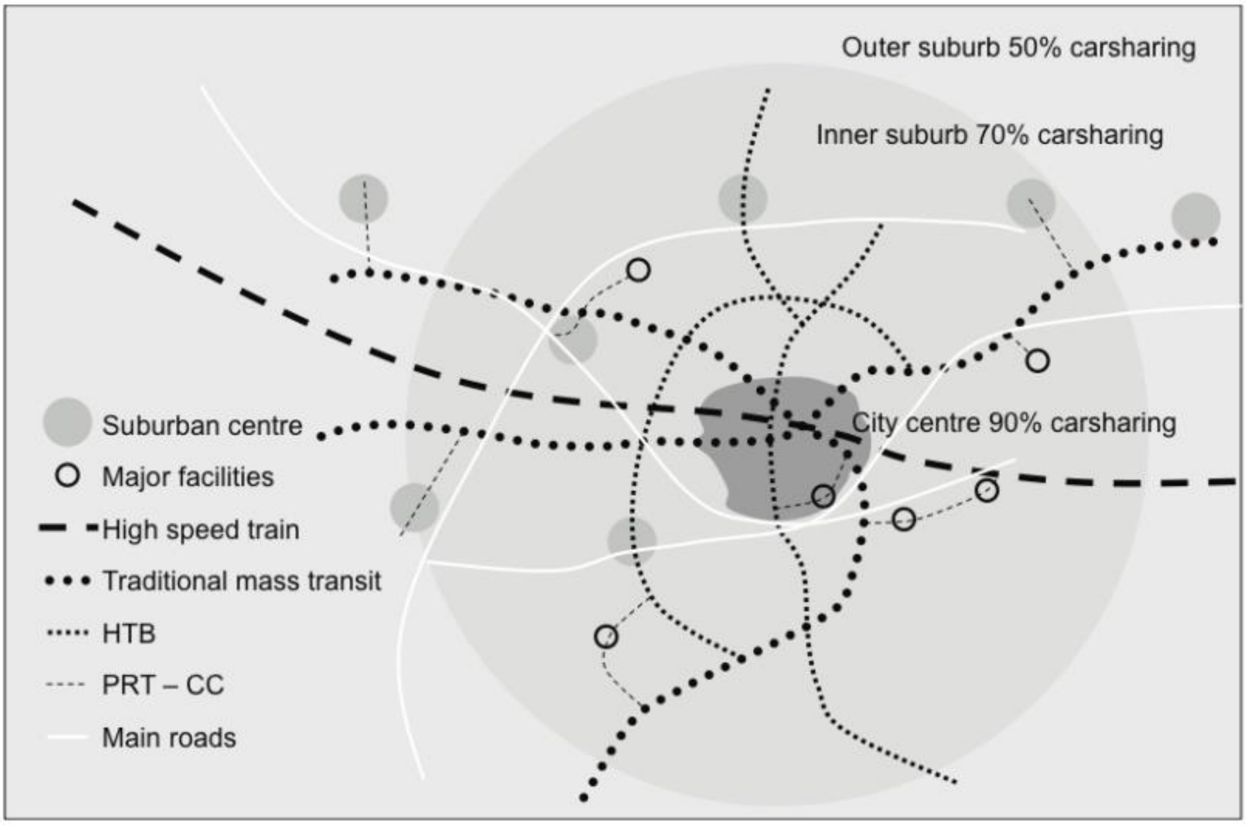


Figure 2.2: The city of the future and it’s transportation system. Source: Alessandrini et al., 2015
HTB = High-tech bus
PRT / CC = Personal rapid transit / cyber car (autonomous taxis)

2.2.4 The environment

In the developed world, around 21% of all energy demand comes from road transportation of persons and goods (Rodrigue & Comtois, 2017). Passenger transportation accounts for 60-70% of this demand and the most used mode in passenger transportation is the private car (Rodrigue & Comtois, 2017). This means that around 8-12% of the total energy demand in developed countries can be attributed to private car travel, with the main source of this energy being fossil fuels. Fossil fuels are becoming increasingly scarce and in the combustion process, many particulates and toxic gasses are emitted, deteriorating air quality near infrastructure. Moreover, the emission of carbon dioxide (CO^2) accelerates the 'greenhouse effect', which causes global warming. It can therefore be concluded that car travel has a considerable negative impact on the environment and therefore human wellbeing.

AVs have the potential to substantially reduce the energy consumption and emission of cars. Chester & Horvath (2009) estimate that an AV would use 12% less energy (Joule) than a similar, non-automated vehicle and has approximately 34% reduced emission of CO^2. There are several arguments why AVs could reduce energy consumption. Firstly, AVs can maintain a shorter headway, reducing drag and decreasing fuel consumption by up to 30% (Alessandrini et al., 2015). Secondly, connected AVs could potentially eliminate the need for intensive braking and accelerating at intersections, by adjusting vehicle speed to that of others on the intersection such that no vehicles have to stop (Fagnant & Kockelman, 2015). Finally, AVs could be manufactured much lighter if the public roads have become safe enough to exclude heavy safety constructions in the vehicle design (Underwood et al., 2014). However, as mentioned earlier, AVs and autonomous taxi's could lead to an increase in vehicle kilometers traveled (VKT). This would of course increase fuel consumption and energy demand.

2.2.5 Personal finance and economy

It has been stated in the introduction that autonomous driving could save the Dutch state billions of euros by preventing road accidents and traffic jams. Apart from that, society could benefit from the developments automated driving will stimulate in the high-tech, automotive and transportation sectors. In Germany, the AV market is predicted to be worth 8.8 billion euros by 2025 (Lutz, 2016). For the consumer, AVs have mixed financial consequences. The initial purchase cost of level 3+ AVs will be very high for now, because state-of-the-art sensors-based technologies currently costs around €75,000 per vehicle (LeVine, 2017). In comparison, most consumers are not willing to pay more than €3000 for autonomous driving (J.D. Power and Associates, 2012a). This indicates that there is of yet a large gap between the demand and supply side, but the general assumption is that automation technologies will become a lot cheaper in the near future (KPMG, 2012). On the long term, automated driving could save car users money because of reduced fuel consumption, declining insurance rates and the potential of car sharing (Litman, 2015).

2.2.6 Social welfare

AVs have the potential to influence the lifestyle of many individuals directly, for better or for worse. For non-drivers, such as elderly, youth and the physically restricted, autonomous driving could offer a flexible transportation alternative, greatly improving their mobility (Sivak & Schoettle, 2015). Besides, affordable autonomous taxis could improve the mobility of low-income households that cannot afford car ownership (Bagloee et al., 2016). However, the utility and accessibility of AVs and autonomous taxis could lead to a decline in active transportation modes such as walking and bicycling, increasing obesity rates (Fagnant & Kockelman, 2015). Furthermore, there are major concerns for people working in the transportation sector, because many are likely to lose their jobs as driver if vehicles become automated (Litman, 2015).

2.2.7 Travel experience

Traveling in an AV will become an increasingly different experience with higher levels of automation, because the driver needs to spend less attention to driving/being alert on the driving environment, meaning they can do other things while travelling such as working, reading, eating etc. (Bansal et al., 2015). Improved driving convenience effectively leads to a lower perceived value of travel time (VTT) (Fagnant & Kockelman, 2015). However, automated driving is not considered a pleasurable experience by everyone. Many people are anxious about transferring driving control to a machine (J.D. Power and Associates, 2012a; Kyriakidis et al., 2015; Schoettle & Sivak, 2014). Furthermore, people who enjoy manual driving will find automated driving boring rather than convenient (Howard & Dai, 2014). Finally, for some groups it may be frustrating or impossible to learn how to use automated driving technology (KPMG, 2013; Lavrinc, 2011).

2.2.8 Summary of opportunities and threats

Table 2.3 summarizes the opportunities and threats of automated driving for society. Some potential impacts may only occur with level 5 automation or with autonomous taxis. These impacts have been marked as such in the table.

Table 2.3: Summary of potential impacts of automated driving on society.
LVL 5 = Impact will only occur with fully automated vehicles
Taxi = Impact will only occur with autonomous taxis

Area of impact	Opportunities	Threats
Safety and security	- Fewer accidents caused by human error	- Bugs, misinterpretation, hacking and terrorism - Interaction between AV and non-AV - Privacy issues - Uncertain liability
Traffic flow	- Smooth vehicle operation - Fewer traffic jams caused by accidents - Improved road capacity	- Extra VKT due to unmanned travel (LVL 5, Taxi) - Slow driving within built-up area - Increased VKT due to utility of AVs
Spatial planning	- Reduced vehicle ownership (Taxi) and automated parking at periphery (LVL 5) lead to lower parking demand	- Increased urban sprawl

Spatial planning (cont'd)	- Repurposing of parking space (Taxi) - Increased potential of multi-modal travel (Taxi)	
Environment	- Fuel efficient driving - Decreased vehicle weight due to safety constructions becoming obsolete	- Increased VKT at the cost of PT usage and cycling
Personal finance and economy	- Reduced economic damages of traffic accidents and travel delay - Opportunities for high-tech and transportation sector - Savings on fuel, parking (LVL 5, Taxi), maintenance and insurance	- High cost of latest technology
Social welfare	- Improved mobility for non-drivers (LVL 5) - Affordable transportation alternative (Taxi)	- Loss of jobs in transportation sector (Taxi) - Declining use of active transportation modes / increasing obesity rates
Travel experience	- Improved travel convenience and productivity	- Loss of driving control / pleasure - Incomprehensible technology

2.3 Stakeholders

Clearly, the range of potential impacts of automated driving is very large. The extent of the impacts logically depends on the market penetration of AVs and autonomous taxis, and therefore on the commercial success of AVs. According to KPMG (2012), the main stakeholders that will determine the success of automated driving are consumers, AV developers and the government.

2.3.1 Consumer

The consumer is important because they must be willing to adopt automated driving. Several researches point out that on average, people have a mildly positive overall attitude towards the use AVs (Howard & Dai, 2014; J.D. Power and Associates, 2012b; Payre, Cestac, & Delhomme, 2014; Schoettle & Sivak, 2014; Sommer, 2013). However, the majority of the people are not willing to pay much extra for automated driving compared to driving a regular, non-automated car (Casley, Jardim, & Quartulli, 2013; J.D. Power and Associates, 2012b; Kyriakidis et al., 2015; Schoettle & Sivak, 2014). Since sensor-based automated driving technologies are currently rather expensive , it is highly uncertain whether consumers will adopt automated driving at higher levels. Main concerns of consumers include the safety and integrity of automated driving technologies, and to a lesser extent privacy and liability issues (Schoettle & Sivak, 2014). Before consumers will adopt automated driving, AV developers and governments must work together to take away their main concerns.

2.3.2 AV developer

AV developers are to a large extent responsible for the image of automated driving. They must prove to the public that automated driving is safe, secure and easy to understand and use. Meanwhile, the cost of AVs must be kept low enough to be commercially attractive. The 'convergence' or combination of sensor-based and connectivity-based technologies in AVs is crucial for these purposes, because it reduces cost while increasing the reliability of automated driving technology (KPMG, 2012). The path to convergence requires a high degree of cooperation between AV developers. Connectivity-based technologies in all AVs, regardless of brand, must be standardized to allow them communicate with each other. The human-machine interface of AVs should also be standardized to some degree, to improve ease of use and familiarity with the technology. Furthermore, a close cooperation of AV developers with the government is needed for the success of AVs.

2.3.3 Government

Currently, level 3+ automated driving is not allowed on public roads in Europe, unless a license has been given for a test project and the roads are sufficiently conditioned. These tests, which are a good example of the cooperation between AV developers and governments, are very important in gaining knowledge about the functioning of AVs in real-life situations and proving the integrity of AV technology. But there are more ways governments could work together with developers. For instance, the two stakeholders could found an official certification system together to ensure the integrity of autonomous driving technology and prevent AV failures which would cause major fallbacks in consumer confidence (Fagnant & Kockelman, 2015). Another important action of authorities could be to issue a mandate that makes the inclusion of information vehicle-to-vehicle (V2V) transmitters in new vehicles compulsory, to support development of connectivity-based technologies (KPMG, 2013). A 'softer' approach to stimulating connectivity-based technologies and automated driving in general, is to offer incentives for manufacturers to include V2V transmitters (KPMG, 2012).

On the other hand, governments must also protect automated driving from society. It is expected that automated driving will lead to changes in behavior of other road users. There is a serious concern that pedestrians and cyclists will take advantage of collision avoidance systems by not giving priority to AVs anymore or jumping in front of AVs for the thrill (Cullen, 2017; Fagnant & Kockelman, 2015). Preventive legislation is necessary to deal with these kinds of problems.

Last, governments must protect society and the consumer from the threats and risks of automated driving. For instance, legislation must be made regarding the liability in case of an accident caused by an AV. This leads to a moral dilemma, because sometimes a crash is unavoidable and in those cases, the AV must make hard decisions, such as whether to endanger vulnerable road users or car passengers (Massachusetts Institute of Technology, n.d.). Other legislation is needed to set up safety standards concerning cyber security of AVs, and to protect the privacy of AV users (Fagnant & Kockelman, 2015). Finally, governments should keep investing in research into the impacts of AVs on society, in order to gain better insight into the threats and anticipate early.

2.3.4 Future of automated driving

In conclusion, governments and AV developers must work together closely to protect and serve consumers and to steer automated driving developments in the right direction. Their interests are intertwined: Governments want automated driving to be a commercial success too, because of it's benefits to society. AV developers want government regulations and control too, in order to prevent scandals and accidents that would hurt the entire industry.

This being said, it is expected that governments will gradually change their legislation towards a higher level of allowance (Netherlands Institute for Transport Policy Analysis, 2017). This means that firstly, level 3+ automated driving will likely only be allowed on certain conditioned roads or road segments, such as dedicated AV lanes. After that, AVs may be allowed on increasingly complex driving environments, from highways to main roads to local roads in residential areas (Boston Consulting Group, 2016). This process will take many years, and full allowance of automated driving in all driving environments may never be feasible. It is assumed however, that in the worst case scenario, automated driving will still achieve a considerable market penetration of 20% by 2040 and 40% by 2050 (Litman, 2015). The Netherlands Institute for Transport Policy Analysis (KiM) estimate that in the Netherlands, level 3/4 AVs will appear on the Dutch main roads by 2025-2045 and level 5 AVs will appear on public roads by 2045-2085 (Netherlands Institute for Transport Policy Analysis, 2017).

2.4 Assessing the impact of AVs on travel demand

The future of automated driving is still very uncertain, but there is no doubt that automated driving will influence the transportation system in the future. The exact impact of automated driving on the transportation system remain very uncertain (Fagnant & Kockelman, 2015). In table 2.3, many arguments why AVs could improve traffic flow are stated, but there are also many arguments for an opposite effect on traffic flow. The impacts of automated driving on the transportation system can be divided into ‘operational’ and ‘behavioral’ impacts. Operational impacts include the effects of improving road capacity, decreasing number of traffic accidents and extra vehicle kilometers traveled (VKT) due to unmanned AV travel. Behavioral impacts include the satisfaction of latent travel demand of non-drivers, higher modal share of cars, higher overall travel demand, changing work- or home location and shopping/leisure destination and changing time of departure. Especially the behavioral impact of automated driving on the transportation system is very uncertain (Gruel & Stanford, 2016). A frequently used tool to assess the behavioral impact of automated driving are travel demand models.

This chapter will briefly explain the principles of travel demand modeling. Secondly, the issues with modeling automated vehicles are discussed. Thirdly, a review will be given of literature on the topic of AV modeling, with implications for travel demand. Finally, the main limitations of AV-related travel demand research will be discussed.

2.4.1 Principles of travel demand modeling

Travel demand models are used to simulate trips made by individuals within a transportation context, which is usually a digital representation of a transportation network. Therefore, the model must predict which trips individuals will make, which transportation mode they will use and which route to take (travel demand). The currently leading type of travel demand models are ‘activity-based’ models. These models assume that the leading source of travel demand are activities that an individual wants to make over a certain period of time. Some activities may be obligatory, such as work. Other activities may be more flexible, and can be decided to be postponed or skipped. Decisions regarding the scheduling of flexible activities and transportation mode choice are usually simulated within the travel demand model using discrete choice models. These models can predict which alternative an individual would choose based on a number of factors that determine the ‘utility’ of each alternative for that individual. A higher utility naturally leads to a higher chance of that alternative being chosen by the individual. Of course, not all individuals aspire the same activities and experience the same utility for all alternatives. Therefore, some models have personalized the available alternatives and utility of those alternatives based on the socio-demographic characteristics of individuals. This is why it is important to research the relations between personal characteristics and travel-related behavior.

After all activity patterns and transportation mode preferences have been determined, routes must be assigned in the model. Road capacity restraints in the transportation network make this procedure iterative: If more individuals choose their routes to go over the same road segments, traffic there will be slower and travel duration will increase for that route choice. This decreases the utility of that route and increases the relative utility of alternative routes with less traffic, causing some individuals to change their route choice. After these changes, the usage of road segments has changed and new travel durations / utility values will be calculated. This process repeats until no individual can improve the utility of their current route choice by changing to another route. This optimized situation is called ‘user equilibrium’. The equilibrium represents the most likely outcome according to the model and can be used to forecast traffic intensities at specific road segments at a certain time, modal shares, etc.

When testing policy implementations, potential infrastructure developments or behavioral/operational changes due to new transportation technologies, two scenarios are created within the travel demand model. One scenario represents the ‘base-case’, for instance the current real-life situation. The other scenario is the same except for the addition of the issue that is under investigation. The difference in outcome between the two scenarios represents the impact of the issue.

2.4.2 Modeling automated vehicles

In order to simulate the travel with AVs, some changes have to be made to conventional travel demand models. Firstly, the size and type of the fleet of AVs must be determined (how many individuals / who has access to an AV). The ‘type’ refers to the level of automation of vehicles in the fleet, and whether they are privately owned or (publicly) shared. The type is important to define because some automation levels have unique technical capabilities such as unmanned travel . Fleet size can be chosen to represent a certain market penetration scenario, or all vehicles can be replaced by AV to analyze the maximum impact.

Conventional travel demand models can only assign routes to individuals (travelers) and not empty vehicles, so a new approach is needed to simulate the phenomenon of unmanned travel. Furthermore, some AVs may be able to maintain a shorter headway to make more efficient use of road capacity. This too requires changes to be made in model specifications.

Apart from these operational impacts of automated driving on the transportation system, there are the behavioral impacts that can be simulated. In order to simulate the satisfaction of latent travel demand of non-drivers, driving constraints for these individuals must be lifted for travel with AVs. Other behavioral changes mostly result from the improved utility of traveling per AV, for instance because they are safer, faster or cheaper than other transportation modes. In order to simulate the effects of this high utility, modelers generally lower the ‘value of travel time’ (VTT) of traveling per AV. VTT can be described the amount a person would spend to reduce travel time by one minute, or in other words, the disutility per minute of traveling with a specific transportation mode. For example: If the VTT of an AV is 0.5 times the VTT of a regular car, the disutility of 10 minutes of traveling per AV equals the disutility of 5 minutes of traveling per car. Logically, this situation would lead to more travel with the AV.

2.4.3 Recent models and implications

Several modeling attempts have been undertaken to simulate the impacts of automated driving on the transportation system. A summary of recent models and their implications for travel demand can be seen in appendix 1. The results of the models show that automated driving is likely to increase travel demand drastically. For example, the Boston Consulting Group (2016) estimates that if most vehicles used were level 5 AVs, the total amount of vehicle kilometers travelled (VKT) in the Amsterdam region would increase by 20% (if automated driving is only allowed at highways) to 100% (AVs allowed on highways and main roads, some AVs are autonomous taxis). The highest reported VKT increase is 190% (Correia & van Arem, 2016). In the corresponding scenario, All vehicles are level 5 private AVs, parking policies have changed so that free parking is only possible at a small number of peripheral nodes, and the VTT of AV travel is halved compared to regular car travel. The other models presented in appendix 1 report more tempered impacts on travel demand. For instance, Childress et al. (2014) indicate an increase in VKT of 5% in the Puget Sound Region (Washington, USA) if all vehicles would be level 3/4 private AVs, road capacity would be increased by 30% and the VTT of AV travel would be reduced by 65%.

Furthermore, some models indicate a change in modal shares. According to the Boston Consulting Group (2016), public transportation (PT) in Amsterdam usage is expected to decline by 48% if automated driving is only allowed on main roads and highways, and by 68% if automated driving is allowed anywhere. In these models, bicycling is expected to decline by respectively 27% and 30%. Kröger et al. (2016) predict a decline in PT usage of 11% in a scenario where 5% of the households own a level 3/4 AV and 38% owns a level 5 AV, with a small reduction in the VTT for AV travel. The only study that suggests an increase in PT usage due to automated driving, is the one from Childress et al. (2014). In the corresponding scenario, all vehicles are level 3/4 AVs and the capacity of highways and main roads in improved by 30%, but no change in VTT of AVs is assumed. The improved use of PT can indicate that AVs may be used for multi-model travel.

2.4.4 Model limitations

Most models clearly focus on one or several impacts of automated driving. Reports with a more holistic approach are rare (Gruel & Stanford, 2016). Furthermore, there is very little evidence for the existence and extent of the behavioral impacts of automated driving (Gruel & Stanford, 2016). The only research in this review that used statistical evidence for the change in modal shares, is the one conducted by the Boston Consulting Group (2016). They used the results of a questionnaire with 489 respondents as input for their model. The results of this survey can be seen in figure 2.3. The question asked to the respondents in this survey is: ‘Which transportation mode would you use during peak times if automated driving could be done anywhere?’ The respondents were also presented with an estimated trip cost per AV. The results of the survey indicate that 60% of current car users, 50% of train users, 70% of bus/subway/tram users and 30% of cyclists would switch to AV, of which approximately 50% would choose for a privately shared AV or autonomous taxi (Boston Consulting Group, 2016).

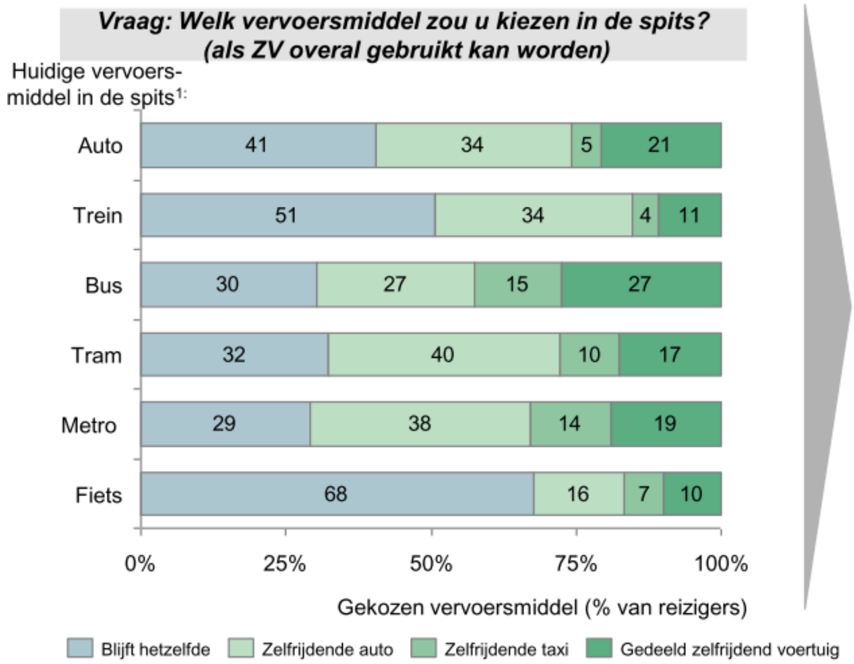


Figure 2.3: Results of survey about tranpsortation mode choice. Source: (Boston Consulting Group, 2016)

Another issue with recent models is that the behavioral impacts are represented in a very generalized manner. By lowering the VTT of AV travel by the same amount for all individuals, changes in preference between those individuals regarding automated driving are disregarded. Also, the willingness to change travel-related behavior due to AVs could vary in different travel contexts, such as short-long trips and work- or shopping trips (Megens, 2014; Voermans, 2015). Therefore, research is needed into the relations between socio-demographic / contextual factors and the behavioral impacts of automated driving. This study will attempt to fill this research gap by searching evidence for the impacts of automated driving on travel demand, and investigating which factors are related to these impacts.

2.5 Factors related to the impact of AVs on travel demand

This chapter contains a literature study to predetermine which factors are most likely related to the impacts of automated driving on travel demand. The resulting factors will be used in the research as explanatory variables. The factors are derived from studies on the topic of ‘consumer acceptance’ of automated vehicles (AVs). This topic is related to the impact of AVs on travel demand, because the ‘actual usage’ of AVs can be considered as an advanced level of the ‘acceptance’ of AVs (Adell, 2007). Therefore, it is likely that the same factors may be relevant. The review distinguishes three types of factors: Attributes of the AV, traveling context and socio-demographic characteristics.

2.5.1 Attributes

Attributes of the AV are characteristics that are (likely) related to the way individuals perceive the utility of an AV. The willingness to use AVs seems to be higher towards lower levels of automation, because people generally do not like the idea of a machine performing their driving tasks (KPMG, 2013; Megens, 2014; Voermans, 2015). Furthermore, a considerable amount of people distrust advanced technology in general (Lavrinc, 2011). One of the main benefits of automated driving according to the consumer is improved travel safety (Howard & Dai, 2014; J.D. Power and Associates, 2012b; Schoettle & Sivak, 2014). A majority believes that automated driving will indeed reduce the number of crashes (Begg, 2014; Schoettle & Sivak, 2014). Another important benefit of automated driving for consumers is the ability to be productive while travelling (Casley et al., 2013; J.D. Power and Associates, 2012b). Attributes that are in general important for the assessment of utility of any transportation mode are travel time (speed) and travel costs.

2.5.2 Traveling context

The traveling context pertains to environment and characteristics of trips. Driving assistance is especially desired in overwhelming and underwhelming driving situations (KPMG, 2012). The road type that most stimulates willingness to use vehicle automation is the highway (Payre et al., 2014; Sommer, 2013; Voermans, 2015). The willingness to use AV also increases with long distances trips (Kyriakidis et al., 2015; Voermans, 2015). Furthermore, people who live in urban areas are more interested than people living in more rural areas (J.D. Power and Associates, 2012b). It seems logical that the trip motive and currently used transportation modes are also related to changes in travel-related behavior due to AVs.

2.5.3 Socio-demographic characteristics

Several personal characteristics are related to peoples' interest in automated vehicles. Many researchers point out that males are on average more open to autonomous driving than females (Begg, 2014; J.D. Power and Associates, 2012b; Megens, 2014; Payre et al., 2014; Schoettle & Sivak, 2014). Furthermore, young people are more open to automated driving than older people (Begg, 2014; J.D. Power and Associates, 2012b; Megens, 2014). Kyriakidis et al. (2015) state that people with a higher income are on average more interested in using autonomous vehicles. Furthermore, people who own a premium-brand vehicle are more interested in autonomous vehicles than people who own 'mass-market' vehicles (J.D. Power and Associates, 2012b; KPMG, 2013).

2.6 Literature study conclusion

Automated driving in general, and level 5 automated vehicles (AVs) and autonomous taxis in particular, show great promise in making transportation safer and more efficient. Several studies forecast that automated driving will gradually penetrate the transportation market until in a final stadium, most vehicles driven will be automated (Litman, 2015; Netherlands Institute for Transport Policy Analysis, 2017). It is plausible that at this time, a large share of the vehicles will not be privately owned anymore but replaced by autonomous taxis (Tillema et al., 2015).

It is further expected that automated driving will have an increasingly large impact on society as market penetration increases. The impact will be noticeable in the fields of road safety, traffic flow, infrastructure and spatial planning, personal finances and economy, the environment, social welfare and travel experience. There are still many uncertainties about the future impacts of AVs and in order for authorities to be able to anticipate to their threats and opportunities, it is important to improve knowledge about the impacts of automated driving.

One of the most uncertain impacts of automated driving is on the transportation system, because there are many arguments why AVs could both have positive and negative effects on traffic flow. The benefits of automated driving include better use of road capacity, less accidents and smoother driving, but on the other hand, unmanned travel, improved travel utility and urban sprawl could lead to a large increase in car usage. Therefore, the future demand for infrastructure is very uncertain and more research is required to estimate the impacts of automated driving on the transportation system more accurately.

This study aims to fill part of this research gap by trying to find statistical evidence for changes in travel demand due to the availability of AVs or autonomous taxis. Previous research indicates that aspects of travel demand that could be influenced due to automated driving are: Modal shares (Boston Consulting Group, 2016; Childress et al., 2014; Gucwa, 2014; Kröger et al., 2016), trip frequency (Childress et al., 2014; Gruel & Stanford, 2016; Pendyala & Bhat, 2014) and trip length (Gruel & Stanford, 2016; Gucwa, 2014; Pendyala & Bhat, 2014). These three concepts will be used in this research as dependent variables to represent changes in 'travel demand'. Factors that are likely related to the impact of automated driving on travel demand are the attributes of automated driving (level of automation, ownership, safety, travel speed and travel costs per kilometer), the traveling context (trip length, trip motive, travel environment, currently used transportation mode) and socio-demographic characteristics (age, sex, income, car ownership, make of the car, household size). These factors will be used as explanatory variables in this research. Figure 2.4 shows a conceptual model that visualized the relations between concepts that will be tested in this study.

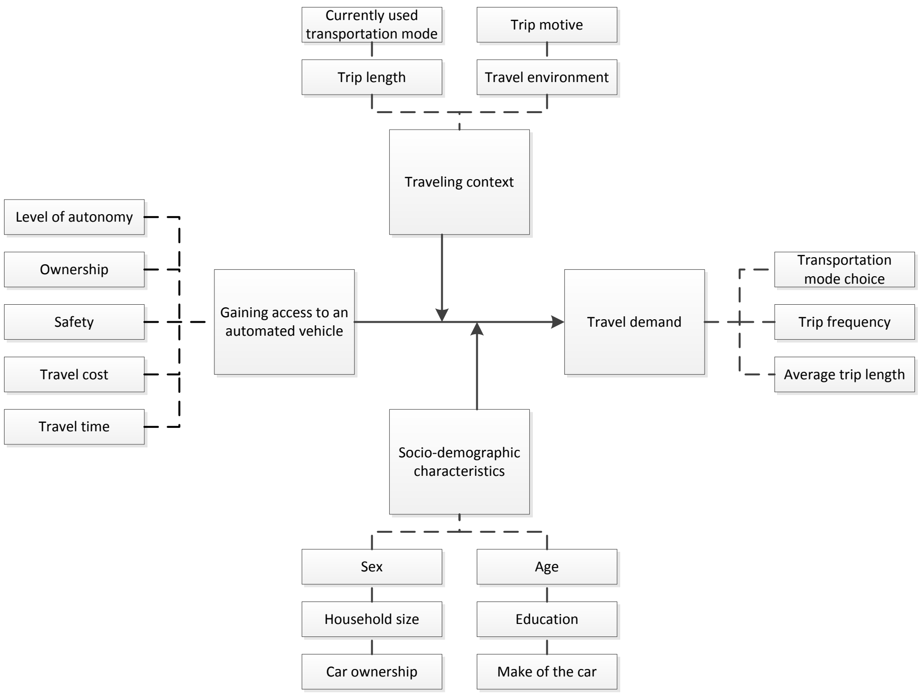


Figure 2.4: Conceptual model

3. Research approach

The main research question of this study is:

What is the impact of automated driving on travel demand and which factors influence this relationship?

The nature of this research will be quantitative in order to determine parameters for effects on different aspects of travel demand and to enable the use of statistical models. The basic approach is to compare current travel-related behavior of individuals with changes made in transportation mode choice, travel frequency and average trip length after gaining access to an AV. The traveling context will be based on real-life trips made by individuals. It is not possible for this study to use existing or observed data, because private usage of AVs (LVL 3+) is not legal currently. Therefore, a stated preference experiment will be conducted to collect data. This means subjects of the experiment must pretend they have access to an AV and state how this would affect them.

One of the advantages of using real-life trips as context instead of a fictional context, is that the results for the impact of AVs travel demand can also be projected on real life. Therefore, it enables the study to give valuable information about the impact of automated driving on the transportation system. A disadvantage is that by using real-life trips, the context cannot be controlled by the experiment designer and therefore it is harder to isolate the effects of automated driving and other factors, because for example, habits and prejudice can play a role in decisions based on real-life cases.

This chapter will discuss consecutively: the experiment design, data collection method and design (an online questionnaire) and data analysis approach.

3.1 Experiment design

Stated preference is an umbrella term for a number of data collection methods. Hensher, Rose, & Greene (2005) describe a stepwise procedure for picking the right stated preference method and setting up the experiment. Their book ‘Applied Choice Analysis: A Primer’ is used as a guide for designing the experiment. The steps followed in the coming sub-sections can be seen in figure 3.1.

3.1.1 Problem refinement

The goal of this study is bilateral. Firstly, it is to determine the impact of automated driving on travel demand in terms of modal shares, travel frequency and average trip length. Secondly, it is to determine which factors influence these impacts. The factors that are under investigation are AV attributes, socio-demographic characteristics and the traveling context.

The traveling context used for the experiment will be a number of recurring trips of the respondent, categorized by trip motive. By using recurring trips, trip frequency per destination can be measured which is one of the dependent variables in this study. The trip motives covered in the experiment are work/education and non-grocery shopping. Work and education activities have been chosen as a category because they account for approximately 29 % of all trips made and are therefore one of the main trip motives in the Netherlands (OViN 2015). Non-grocery shopping has been selected as a representative of (semi-)recreational trips, which also represent a large share of total trips. These trip

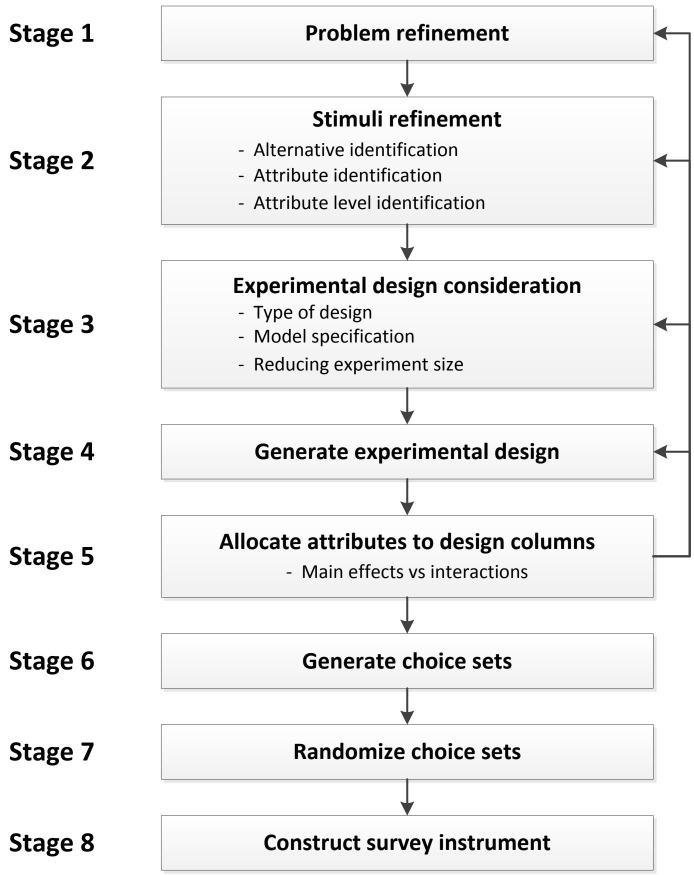


Figure 3.1: Stages of designing a stated choice experiment. Source: Hensher et al. (2005)

motives are further deemed suitable for the stated choice experiment, because trips with these motives occur rather frequently (respectively 4 and 1 time per week on average for work and non-grocery shopping) and are long enough on average so that the AV can be a viable transportation mode alternative (resp. 14 and 3 km one-way trip length on average for work and non-grocery shopping) (Snellen, 2002).

It would be too complicated for this experiment to also include long-term decision effects such as car ownership and home- or work location choice. Therefore, subjects do not need to decide whether or not they would want to buy an AV, but must pretend they already have one. Furthermore, average trip length, one of the dependent variables, will only be based on non-grocery shopping trips. This is because average trip length depends on location choice, and changes in home- and work location choices are not be covered in the experiment.

3.1.2 Stimuli refinement

In this second stage of the experiment design, the alternatives, their attributes and attribute levels are refined. Alternatives are the entities that an individual has to consider before stating their preference. In this experiment, the only relevant alternative is the AV. The AV in the experiment will have several attributes that have been derived from the literature: Level of automation, ownership, safety, travel time and travel costs.

The attributes are still rather ambiguous and need to be refined. Furthermore, several levels have to be determined per attribute. An attribute level represent the state or value of that attribute. For instance, the attribute 'vehicle color' could have the levels: 'blue', 'red', 'black', etc. The attribute levels will be used to define the AV in the experiment. Only a selection of all possible levels of the attributes will be used in the experiment. Choosing the number of levels per attribute is a trade-off decision. More levels provide increasingly can comprehensive information about the attribute, but they also require a larger sample size to be analyzed properly and increase the risk of overlapping interpretation between levels, rendering some of them irrelevant. For this study, it has been decided to use a maximum of three levels per attribute. Each attribute and their attribute levels will be substantiated in the following sub-paragraphs.

Attribute: Level of automation

The level of automation refers to an index describing the technical capabilities of AVs (SAE International, 2014). Many impacts of automated driving, including some effects on travel-related behavior, only manifest themselves with higher levels of automation. For instance, car usage is believed to considerably increase once travelers do not have to pay full attention to driving anymore, which is only possible from level 3 onwards. Besides, only level 5 AVs can be used for automated (unmanned) parking and driverless taxi's. For these reasons, it has been decided to only include level 3 and higher AVs in the experiment, because they have a bigger chance of influencing travel demand.

Level 3 and 4 may appear very similar for those who are unfamiliar with the concept of automated driving, and are therefore merged into a single attribute level. In order to avoid presenting an extensive list of technical capabilities to respondents, the descriptions in table 3.1 have been used to describe level 3/4 and level 5 AVs in the experiment. The descriptions are based on terminology used by the KiM (Netherlands Institute for Transport Policy Analysis, 2017)

Table 3.1: Definition of attribute levels of 'Level of automation'

Level	Definition
Level 3/4 AV	This AV can drive autonomously on highways and main roads, so attention can be averted from the driving task. Manual driving required within the built-up area.
Level 5 AV	This AV can drive autonomously anywhere, so attention can be averted from the driving task.

Attribute: Ownership

There are three major categories of AV ownership: Private ownership, shared ownership and autonomous taxis. The utility of the latter two forms is based on unmanned travel, which is only possible with level 5 automation. Shared ownership will not be included in the experiment, because it is too complicated to represent the car availability limitations of shared ownership in the questionnaire. This leaves 2 attribute levels: Private ownership and autonomous taxis.

Since it makes no sense to combine the attribute level 'Autonomous taxi' with 'level 3/4 AV', the attributes 'level of automation' and 'ownership' will be combined into a single attribute called 'type', to prevent this combination from occurring in the experiment. The resulting, combined attribute levels remaining are: Level 3/4 private AV, Level 5 private AV and autonomous taxi.

These attribute levels mean that in some cases in the experiment, a subject must pretend they own an AV. However, these individuals may already own a car. Therefore, it is stated in the experiment that if an individual already has a car, the private AV will be a similar car (with automation features) that replaces their current vehicle. The definitions of the attribute levels of the attribute 'type' that are used in the experiment can be seen in table 3.2.

Table 3.2: Definition of attribute levels of 'Automated vehicle type'

Level	Definition
Level 3/4 private AV	AV that is only used by the respondent and their household members. It can drive autonomously on highways and main roads, so attention can be averted from the driving task. Manual driving required within the built-up area.
Level 5 private AV	AV that is only used by the respondent and their household members. It can drive autonomously anywhere, so attention can be averted from the driving task.
Level 5 autonomous taxi	Autonomous taxi without chauffeur that has a quick response time. It can drive autonomously anywhere, so attention can be averted from the driving task.

Attribute: Safety

The safety of a vehicle will be expressed as the chance of an accident while traveling. It is hard to find a sensible value for the chance of an accident that can be fully appreciated by the respondent. Therefore, the chance of an accident will be expressed as an improvement percentage relative to the chance of having an accident with a regular, non-automated car.

The first level of this attribute will serve as a reference and will be 'same chance of having an accident traveling as a regular vehicle'. The second and third level will respectively be a small and large improvement of 25 and 75% less chance on an accident. The definitions of the attribute levels of the attribute 'safety' can be seen in table 3.3.

Table 3.3: Definition of attribute levels of 'Safety'

Level	Definition
Equally safe	Similar chance on accident while traveling as regular vehicles
25% improved safety	25% less chance on an accident while traveling than regular vehicles
75% improved safety	75% less chance on an accident while traveling than regular vehicles

Attribute: Travel time

The travel time (speed) of the AV will also be expressed as an improvement percentage related to regular car travel. In the questionnaire it will both be presented as a percentage difference compared to regular car travel, and as the change in travel duration compared to the travel duration with the currently used transportation mode, in minutes. To calculate the travel duration in minutes of the AV, the 'average one-way door-to-door travel time per car' (TTC) is doubled (to represent two-way trip) and a small amount will be added or subtracted, based on the attribute level.

To calculate the expected travel duration improvement with the AV in minutes, the travel duration experienced with the current main transportation mode is subtracted from the AV travel duration. If the resulting amount is negative, there is a travel time improvement. If the result is positive, travel time with the AV is longer. It is required that individuals state their current travel time with their main transportation mode *and* per car, for each destination. If they never travel to a particular destination by car, they must estimate the TTC.

Attribute levels

The first level of 'travel time' will serve as a reference and will be a similar travel time as a regular vehicle. The second and third levels respectively represent a better and worse travel time than regular car travel. The difference in terms of percentage is chosen to represent a significant, but realistic change of 15% compared to regular car travel. Some explanations are added in the survey to clarify why the AV in the experiment is faster or slower. The definitions of the attribute levels of the attribute 'safety' can be seen in table 3.4.

Table 3.4: Definition of attribute levels of 'Travel time'

Level	Definition
15% shorter travel times	15% reduced travel times compared to regular car travel, due to efficient vehicle operation systems and the ability to use dedicated lanes for automated traffic
Equal travel times	Similar travel times compared to regular car travel
15% longer travel times	15% increased travel times compared to regular car travel, due to cautious driving style of the vehicles' operation systems

ATTRIBUTE: TRAVEL COSTS

Similarly to travel time, travel costs involved in traveling with the AV will be presented in the experiment as an improvement percentage compared to regular cars, and the change in euros for each destination if the individual would travel with the AV instead of their currently used transportation mode. Travel costs are defined in the questionnaire as the *variable* costs related to a two-way trip, namely fuel cost and the variable parts of vehicle depreciation and maintenance expenses. The fixed costs of vehicle ownership are not included in this experiment, because they are not expected to affect mode choice, travel frequency or trip length (it might affect car ownership decisions but that is not within the scope of this research). In case of the AV being an autonomous taxi, travel costs refer to the transportation fee.

The expected difference in trip costs (in euros) with the AV is calculated by subtracting the estimated trip costs of the main transportation mode with the estimated trip costs of the AV. A negative trip cost difference therefore indicates that the usage of the AV is cheaper than the usage of the currently used transportation mode. Trip costs are not estimated by the respondent but calculated using a series of formulas. The calculation of trip costs is rather complicated and consists of three parts: Travel costs, parking costs and compensation.

Travel costs

Travel costs are calculated based on an estimated cost per kilometer multiplied by the trip length in kilometers. Naturally, the cost of walking and cycling per kilometer is 0€. 'Other' transportation modes, one of the answer categories, is also set to 0€.

The variable cost per kilometer for car travel is derived from calculations by Nibud based on the type of car travelled with (see table 3.5). Therefore, respondents will have to state what kind of car they are driving. Higher class vehicles have a higher cost per kilometer. The AV is assumed to be of the same class as the respondent's own car. Therefore, the travel costs of the AV will be calculated based on the same cost per kilometer as the respondents current car, plus or minus a small percentage based on the attribute level. If a respondent has indicated they do not have a car, it is assumed the AV is a 'small middle class' vehicle (€0.19 per kilometer base travel costs).

Table 3.5: Estimated variable costs per kilometer per car class. Source: Nationaal Instituut voor Budgetvoorlichting

Car class	Variable cost per kilometer
Mini class	€0.17
Compact class	€0.19
Small middle class	€0.19
Middle class	€0.22
Large middle class	€0.24
Top class	€0.26

Costs per kilometer for trips made by public transportation (PT) have been estimated at €0.19. This amount is based on the average cost per kilometer for a 30 km trip per train, according to a publication with consumer fares by the Dutch railway company (Nederlandse Spoorwegen, 2017). If PT has been selected as main transportation mode for a certain destination, the respondent has to state whether they own a discount membership and receive a fare reduction during their trips to the corresponding destination. The discount received has to be selected from a list of the most common reduction rates in the Netherlands: 20%; 40% or 100%(free). This value is used to reduce the cost per kilometer for PT travel accordingly.

Estimating trip length in kilometers may be hard for many respondents as well. Therefore, trip length is calculated based on a function. Two different functions are used to calculate trip length in kilometers for car and PT travel. The functions have been estimated with the use of two datasets that consist of travel time calculations by Google Maps Navigation for 100 car trips and 100 PT trips of various trip lengths. The 'curve estimation' function of SPSS has been used to select the best fitting equation for the functions (exponential), and the parameter values for the functions have been estimated by a regression model in SPSS. The resulting functions can be seen below.

Function used for calculating trip length in kilometers with PT:

$$TD_{PT} = 0.25 * (TT_{PT})^{1.35}$$

Where:
TD_{PT} = Estimated door to door travel distance in kilometers with main mode = PT
TT_{PT} = Door to door travel time in minutes with PT

Function used for calculating trip length in kilometers with car:

$$TD_{car} = 0.3 * (TT_{car})^{1.35}$$

Where:
TD_{car} = Estimated door to door travel distance in kilometers with main mode = car
TT_{car} = Door to door travel time in minutes with car

Parking costs
In case of trips by car or private AV, there may be parking costs involved. Respondents are requested to state average parking cost per visit for all destinations considered in the questionnaire. If the respondent indicates that they don't know the parking costs of a location, a fee per visit will be estimated for them based on the location type. For a work or education location, the parking cost will be set to 0€, unless the respondent has indicated that there is paid parking (but they're not sure how much), in which case the estimated cost per visit is €5. For shopping locations, parking fees are estimated based on shopping center type visited. These estimated amounts can be seen in table 3.6.

Table 3.6: Estimation of parking costs per visit for different shopping center types

Shopping center type	Parking fee
Local- or neighborhood center (small scale, basic needs)	€0.5
District center (medium sized, miscellaneous stores)	€2
Local center / single store (central, expansive, leisure oriented)	€5
Themed center (medium or large sized, specialized)	€1
None of the above	€0

Some AVs in the experiment have parking benefits. The level 5 private AV can use automated, unmanned parking to park in less expensive locations. To represent this, all parking costs involved for level 5 private AVs has been halved. Level 3/4 private AVs cannot park themselves unmanned, so their parking fees will remain at 100%. There are no parking costs involved when travelling with the autonomous taxi.

Compensation
For trips made to a location of a fulltime / part-time job or a part-time education, it could be possible that travel expenses are compensated for by an employer. Respondents can indicate that all of their travel expenses are compensated, after which both travel and parking costs of all transportation modes for that destination are set to 0€. Alternately, they can indicate a compensation fee per kilometer, which is a common practice in the Netherlands. This amount is subtracted from the cost per kilometer of car, PT and AV travel before calculating the travel costs.

Attribute levels
The first level of the attribute 'travel costs' will serve as a reference and will be 'similar travel costs as a regular vehicle'. The second and third levels respectively represent a better and worse travel costs than regular car travel. Travel cost improvements could occur because of improved fuel economy and decreasing insurance rates for AVs, and travel cost increase could occur because of higher maintenance costs due to the expensive technological equipment used in AVs. The difference in terms of percentage is chosen to represent a significant, but realistic change of 15% compared to

regular car travel. The definitions of the attribute levels of the attribute 'travel costs' can be seen in table 3.7.

Table 3.7: Definition of attribute levels of 'travel costs'

Level	Definition
15% cheaper	15% reduced variable travel costs compared to regular car travel
Equal travel costs	Similar travel times compared to regular car travel
15% more expensive	15% increased variable travel costs compared to regular car travel

Summary of attributes

Table 3.8 shows a summary of all attributes and their definitions. Table 3.9 shows a summary of all attribute levels per attribute. This table includes a tag for each attribute level which will be used to refer to the level further on in this report.

Table 3.8: Summary of attributes and their definitions

Attribute	Definition
Level of automation*	Level of automation of the AV on a 5-point scale, as indexed by NHTSA (SAE International, 2014)
Ownership*	Statement of to whom the AV is accessible; Private usage, shared usage, public usage etc.
Safety	The relative chance of having an accident during trips with the AV compared to a similar, non-automated vehicle. Expressed in a percentage.
Travel time	The relative, average travel time from door to door trips with the AV compared to a similar, non-automated vehicle. Expressed in a percentage.
Travel costs	The relative, variable travel costs of traveling by AV, compared to those of a similar, non-automated vehicle. Expressed in a percentage

** Combined into single attribute 'Type'*

Table 3.9: Summary of attributes levels per attribute

Attribute	Level	Name	Tag
Type	1	LVL 3/4 private AV	LVL 3/4
	2	LVL 5 private AV	LVL 5
	3	LVL 5 autonomous taxi	Taxi
Safety	1	Equally safe to regular cars	Normal
	2	25% less chance on an accident	Safer
	3	75% less chance on an accident	Much safer
Travel time	1	Equally fast to regular cars	Faster
	2	15% faster than a regular car	Normal
	3	15% slower than a regular car	Slower
Travel cost	1	Equally expensive to regular cars	Expensive
	2	15% more expensive than a regular car	Normal
	3	15% cheaper than a regular car	Cheap

3.1.3 Experiment type consideration

The next consideration is which type of response variables to use. There are three types of response variables to choose from in stated preference experiments: Rating, ranking and choice (see figure 3.2). Response variables refer to the variables used in the experiment, to represent dependent variables used in the analysis.

The dependent variables used are: changes in transportation mode usage, travel frequency and average trip length. Average trip length however, is not so much a decision but rather a result of the chosen trip frequencies to different destinations. Therefore, average trip length will not be explicitly asked from the respondents, but instead will be calculated based on the response variable 'travel frequency'.

The two remaining response variables, referring to transportation mode usage and travel frequency, are a choice rather than an appreciation (preference), and are therefore choice-type variables. For determining transportation mode usage, the respondents has to choose a usage percentage of the AV per destination. They can choose for one of the answer categories from table 3.10. This AV usage will be compared to currently used transportation modes to calculate changes in modal shares. This procedure is explained in chapter 3.3.1. For travel frequency, respondents must choose from a list of suggested frequencies. The 'new' frequencies will be compared to the current travel frequency per destination to calculate difference in travel frequency. The list of answer categories for travel frequency is adjusted to the trip motive, meaning the answer categories will be different for work/education destinations (table 3.11) and non-grocery shopping destinations (table 3.12).

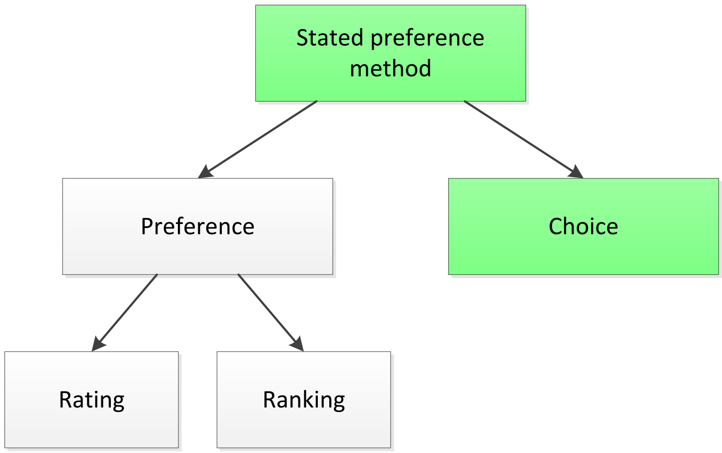


Figure 3.2: Types of stated preference methods

Table 3.10: Answer categories for 'AV usage percentage' per destination

List of usage rates	Numerical value
100% of trips	1
90% of trips	0.9
80% of trips	0.8
70% of trips	0.7
60% of trips	0.6
50% of trips or less	0.5

Table 3.11: Answer categories for 'Trip frequency' for work/education destinations

Answer category	Value
less than once per week	0
1 x per week	1
2 x per week	2
3 x per week	3
4 x per week	4
5 x per week	5
6 x per week	6
7 x per week	7
8 x per week	8
9 x per week or more	9

Table 3.12: Answer categories for 'Trip frequency' for non-grocery shopping destinations

Answer category	Value
less than once per half year	0
1 x per half year	0.038
1 x per 3 months	0.077
1 x per month	0.23
1 x per 2 weeks	0.5
1 x per week	1
2 x per week or more	2

3.1.4 Reducing experiment size

Each AV presented in the experiment will have a combination of four attribute levels, one from each attribute. A unique combination of attribute levels is called a 'profile'. For example: A level 5 private AV, that is equally safe, fast and expensive as a regular car counts as one unique profile. With the amount of attributes and attribute levels in this experiment, 3^4 = 81 unique profiles can be made. The selection of all possible profiles to be used in the experiment is called 'full factorial design'. However, it is possible to reduce the amount of profiles used in the experiment (resolution) while still being able to determining the effects of each attribute level. Each additional profile requires a larger sample size in order to generate significant results, so the number of profiles used in choice experiments is often reduced to a fraction of the total: a 'fractional factorial design'. The decision for a resolution is a trade-off, because smaller factorial designs provide less reliable information about interaction effects (NIST/SEMATECH, 2012). Interaction effects are the effect an attribute level has on the dependent variable, if it is paired with one or more other attribute levels. For instance, the effect of a level 5 autonomous taxi on mode choice, *but only* if it is cheaper than a regular vehicle. The opposite of interaction effects are main effects, which represent the direct effect of an attribute level on the dependent variable.

Fractional factorial designs are constructed based on the principle or orthogonality. This technique is used to create minimal correlation between (combinations of) attribute levels, by pairing each attribute level equally often with any other attribute levels. If this would not be the case, for example if 'level 5 autonomous taxi' would be paired more often with '15% faster travel times' than '15% slower travel times', the results would be biased because taxis will become associated with a travel time benefits. For this study, the choice has been made to use the minimal design resolution needed to estimate main effects. This fractional factorial design consists of 9 profiles and features each pair of attribute levels exactly once. The consequence is that no interaction effects can be estimated, because if a pair of attribute levels only occurs in a single profile, the other attributes of that profile have fixed levels which will cause a bias when analyzing the interaction effect. Also, the main effects could still be slightly biased by second degree interaction effects with this resolution. The reason for the choice for a minimal factorial design resolution is that at the time of this decision, the involvement of a market panel had not been anticipated and there was only accounted for a small sample size of 150-200 respondents.

3.1.5 Generating experimental design

In this stage, the fractional factorial design will be generated by selecting 9 profiles. The 'generate orthogonal design' function of SPSS was used for this purpose. The attribute levels of the profiles have also been coded according to the 'dummy coding' principle. Dummy coding essentially replaces a categorical or ordinal scale variable with n-1 dichotomous variables (Booleans), with n being the number of levels within that variable. One of the levels is not converted into a dummy, because this would cause collinearity issues. Moreover, it is unnecessary to generate n dummies because if n-1 dummies report untrue, the last dummy must be true and vice-versa. Dummy coding is essential, because ordinal (non-normally distributed) and categorical variables cannot be used as explanatory variables in regression models as opposed to dichotomous variables. The resulting 9 profiles in dummy coding can be viewed in table 3.13.

Table 3.13: Fractional factorial design

	Type (00=LVL 3/4)		Safety (00=normal)		Travel time (00=normal)		Travel costs (00=normal)	
Profile	LVL 5	taxi	safer	safest	faster	slower	expens.	cheap
1	0	0	0	0	0	1	1	0
2	0	0	1	0	0	0	0	0
3	0	0	0	1	1	0	0	1
4	1	0	0	0	1	0	0	0
5	1	0	1	0	0	1	0	1
6	1	0	0	1	0	0	1	0
7	0	1	0	0	0	0	0	1
8	0	1	1	0	1	0	1	0
9	0	1	0	1	0	1	0	0

3.1.6 Constructing the survey instrument

The last stage is about designing the part of the survey that will cover the experiment. At the start of the experiment, respondents will receive some essential information regarding automated driving. This is because the research simulates a situation in which the respondent has acquired access to an AV and it is logical that once this situation would occur in real-life, the respondent would have gained such knowledge about AVs. The description of AVs includes the definition of automated driving, most important features of AVs and some assumptions that have been made. The length of the description has been limited to only the essential information to decrease questionnaire duration. The full, translated introductory text can be seen below (the original questionnaire is in Dutch).

'Please read the following text before continuing with the questionnaire.

You are approximately halfway through this questionnaire. For the following questions you are required to pretend that you can use a self-driving car or taxi. A self-driving vehicle is:

'A vehicle that is operated by automated driving systems and is capable of transportation without human intervention.'(Wikipedia)

Please assume during this questionnaire that:
- The self-driving car or taxi looks like your current car / a normal car;
- The automated driving systems drive at least as safe as a human driver;
- You will be in possession of a valid drivers' license if you haven't got one already.'

After this introduction, the respondent will have the chance to add an extra shopping destination to their list, that they would consider visiting if they would have an AV. This is the3rd or 4th shopping location depending on the number of shopping locations they indicated earlier in the questionnaire (min. 2 and max. 3).

Next, the respondent will be presented with a trial of the experiment. Using an example is useful because generally respondents need to do several tries before completely understanding the choice task (Hensher et al., 2005). After the trial, the respondent will be presented with three different AV profiles consecutively (three choice tasks). Each AV is presented on a separate page. The fact that there are three choice tasks per person means that at least three respondents have to fill in the survey completely in order to cover all AV profiles once. The low amount of tasks per person has been chosen because each task takes several minutes to complete, and it was decided to limit the expected duration of the survey to 15 minutes.

Each profile should be covered approximately equally often in the experiment to prevent overrepresentation of some profiles, and respondents should never receive the same profile twice. Furthermore, it was decided that each respondent should be presented with at least a level 3/4 private AV, a level 5 private AV and an autonomous taxi. In order to ensure this, the 9 profiles were subdivided into 3 'sets' with 3 profiles each. The profiles within each set were selected so that each one of the three levels of the attribute 'type' is covered once, while the levels for the attributes 'safety', 'travel time' and 'travel costs' would show substantial variation within the sets. Each subsequent respondent will receive three choice tasks based on the profile within a single set. The assignment of sets to respondents is being balanced, ensuring that each set / profile is covered approximately equally often.

The three profiles within a set will be presented to the respondent consecutively, with trivial labels to indicate the progress of the experiment. Sets have been generated manually by combining profiles until a sufficient level of variation between attribute levels within a set was found. The sets and their corresponding profiles can be viewed in table 3.14.

The attribute levels of each AV will be presented to the respondent in a series of brief statements at the top of each choice task page. The translated statements per level are formulated in table 3.15.

Table 3.14: Profile sets used in the survey instrument

Set	Profile	Type	Safety	Travel time	Travel costs	Label
1	1	LVL 3/4	Normal	Slower	Cheap	'A'
	8	Taxi	Safe	Faster	Cheap	'B'
	5	LVL 5	Safe	Slower	Expensive	'C'
2	3	LVL 3/4	Safest	Faster	Expensive	'A'
	7	Taxi	Normal	Normal	Expensive	'B'
	4	LVL 5	Normal	Faster	Normal	'C'
3	6	LVL 5	Safest	Normal	Cheap	'A'
	9	Taxi	Safest	Slower	Normal	'B'
	2	LVL 3/4	Safe	Normal	Normal	'C'

Table 3.15: Description of attribute levels used in the survey instrument

Attribute	Level	Vehicle 'X' has the following attributes:
Type	LVL 5	Vehicle 'X' is your personal property. If you have one or more cars, they will be replaced by the AV. Vehicle 'X' can drive fully autonomous, enabling you to focus on other things while traveling.
	Taxi	Vehicle 'X' is a publicly accessible, self-driving taxi without chauffeur. Vehicle 'X' drives fully autonomous, enabling you to focus on other things while traveling.
	LVL 3/4	Vehicle 'X' is your personal property. If you have one or more cars, they will be replaced by the AV. Vehicle 'X' can drive fully autonomous on highways only, enabling you to focus on other things while traveling. Within the built-up area you must drive manually.
Safety	Safer	'X' has proven to be involved in 25% less accidents than 'regular' vehicles
	Safest	'X' has proven to be involved in 75% less accidents than 'regular' vehicles
	Normal	'X' has proven to be involved equally often in accidents as 'regular' vehicles
Travel time	Faster	'X' drives efficiently and may use certain dedicated lanes, resulting in 15% shorter travel times on average
	Slower	'X' drives very cautiously, resulting in 15% longer travel times on average
	Normal	'X' is with regard to travel times equally fast as a 'regular' vehicle
Travel costs	Cheap	'X' is with regard to travel costs* approximately 15% cheaper than a 'regular' vehicle
	Expensive	'X' is with regard to travel costs* approximately 15% more expensive as a 'regular' vehicle
	Normal	'X' is with regard to travel costs* equally expensive as a 'regular' vehicle

After reading the AV description, the respondent is required to fill in the response variables. The response variables have been defined as: 'The usage rate of the AV per destination, in %' and 'The new travel frequency per destination'.

For a possible 4^{th} shopping location (the location that may have been after the introduction of the AV), usage rate of the AV does not have to be filled in. This is because this locations isn't visited currently, so it is assumed that all trips to this location will be made with the AV.

All questioning and response variables will be presented on the same page so respondents can continually use the AV description as a reference. A table is used to structure information pertaining to individual destinations. They contain the information about difference in travel time and cost with the AV as well as a reference to the respondent's earlier replies regarding their currently used transportation mode and travel frequency. The 2 columns on the right side of each table are reserved for the input of the response variables. Work-/study destinations and shopping destinations are presented separately in two tables. The reason for a separate table for all shopping destinations is the expectation that this will stimulate respondents to make integral choices regarding their travel frequency, meaning they could decide to 'switch' locations by trading travel frequency of one location for the other.

An important part of the choice task design is the formulation of questions leading to the response variables. Two questions are stated above each table; Each pertaining to one of the two response variable types. The questions are formulated as follows (translated from Dutch):

'Question 1/3: How often would you visit these destinations, if you could also use vehicle 'X'?

Question 2/4: How much % of your visits to these destinations would you make with vehicle 'X'?'

Figure 3.4 on the next page shows the entire page containing one task. This image is taken directly from the questionnaire, so the texts are still in Dutch.

3.2 Questionnaire design

The tool used to collect data is an online questionnaire that has an expected duration of 10-15 minutes. The questionnaire was designed with BergEnquete software of the TU/Eindhoven. A significant part of the questionnaire will be the stated choice experiment which has been discussed in chapter 3.1.6. The subsequent sections of the questionnaire are depicted in figure 3.3. The following report sections will discuss the design of each of these sections. Chapter 3.2.8 explains the population targeted and respondents approach.

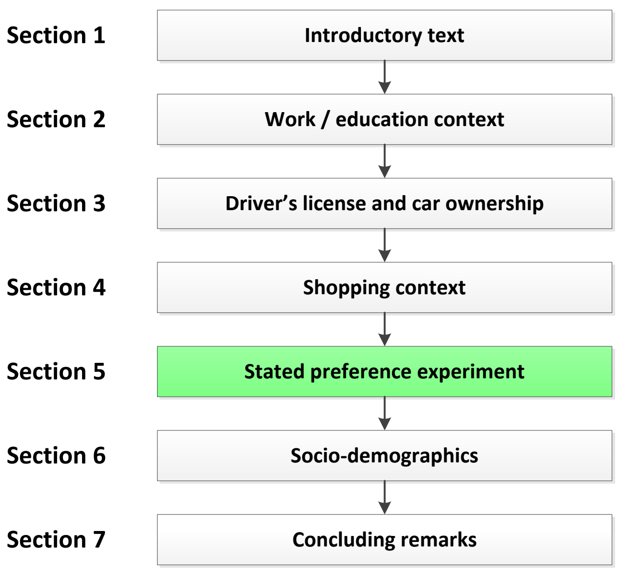
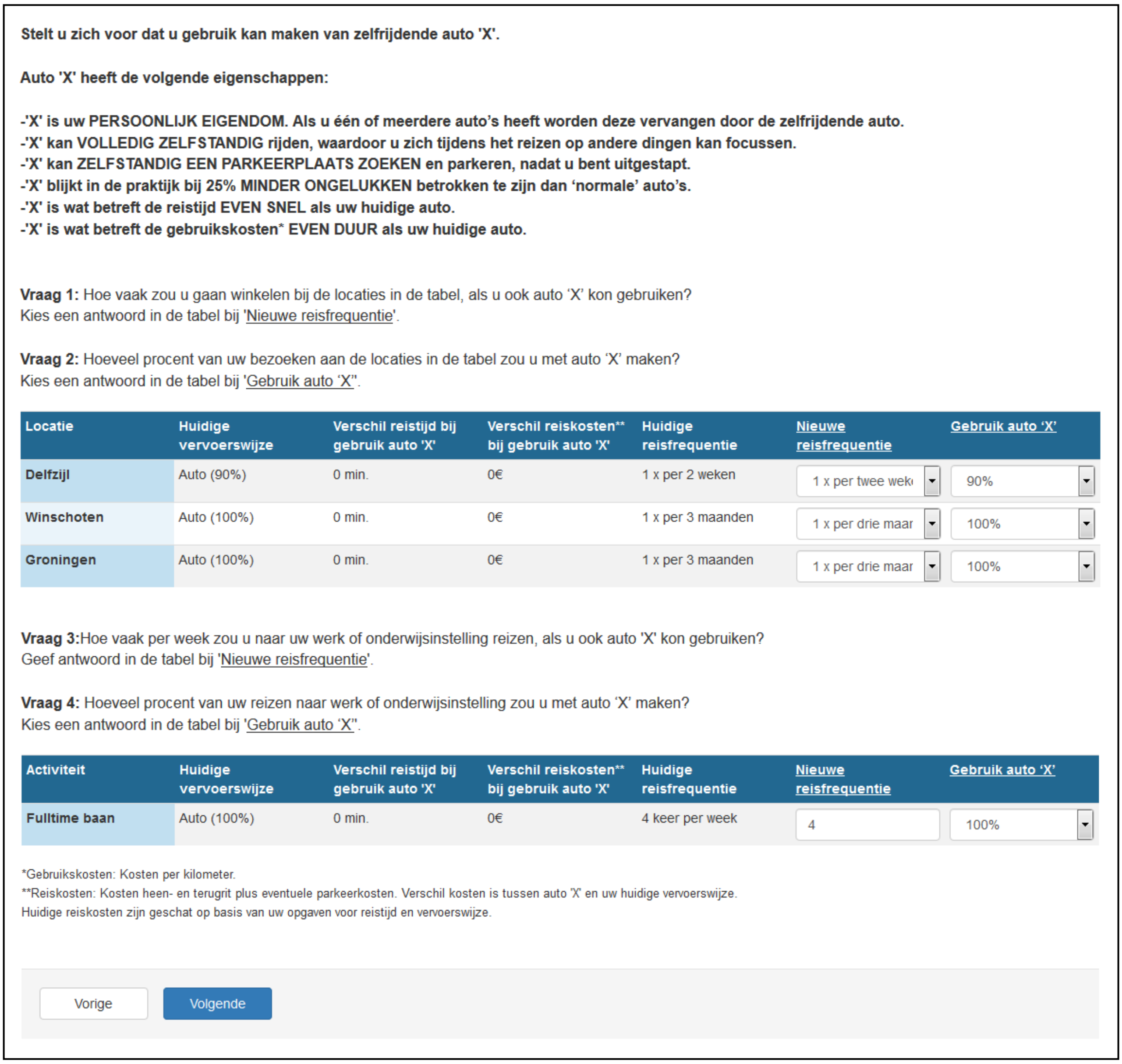


Figure 3.3: Questionnaire sections



Stelt u zich voor dat u gebruik kan maken van zelfrijdende auto 'X'.

Auto 'X' heeft de volgende eigenschappen:

-'X' is uw PERSOONLIJK EIGENDOM. Als u één of meerdere auto's heeft worden deze vervangen door de zelfrijdende auto.
-'X' kan VOLLEDIG ZELFSTANDIG rijden, waardoor u zich tijdens het reizen op andere dingen kan focussen.
-'X' kan ZELFSTANDIG EEN PARKEERPLAATS ZOEKEN en parkeren, nadat u bent uitgestapt.
-'X' blijkt in de praktijk bij 25% MINDER ONGELUKKEN betrokken te zijn dan 'normale' auto's.
-'X' is wat betreft de reistijd EVEN SNEL als uw huidige auto.
-'X' is wat betreft de gebruikskosten* EVEN DUUR als uw huidige auto.

Vraag 1: Hoe vaak zou u gaan winkelen bij de locaties in de tabel, als u ook auto 'X' kon gebruiken?
Kies een antwoord in de tabel bij 'Nieuwe reisfrequentie'.

Vraag 2: Hoeveel procent van uw bezoeken aan de locaties in de tabel zou u met auto 'X' maken?
Kies een antwoord in de tabel bij 'Gebruik auto 'X''.

Locatie	Huidige vervoerswijze	Verschil reistijd bij gebruik auto 'X'	Verschil reiskosten** bij gebruik auto 'X'	Huidige reisfrequentie	Nieuwe reisfrequentie	Gebruik auto 'X'
Delfzijl	Auto (90%)	0 min.	0€	1 x per 2 weken	1 x per twee wek	90%
Winschoten	Auto (100%)	0 min.	0€	1 x per 3 maanden	1 x per drie maar	100%
Groningen	Auto (100%)	0 min.	0€	1 x per 3 maanden	1 x per drie maar	100%

Vraag 3: Hoe vaak per week zou u naar uw werk of onderwijsinstelling reizen, als u ook auto 'X' kon gebruiken?
Geef antwoord in de tabel bij 'Nieuwe reisfrequentie'.

Vraag 4: Hoeveel procent van uw reizen naar werk of onderwijsinstelling zou u met auto 'X' maken?
Kies een antwoord in de tabel bij 'Gebruik auto 'X''.

Activiteit	Huidige vervoerswijze	Verschil reistijd bij gebruik auto 'X'	Verschil reiskosten** bij gebruik auto 'X'	Huidige reisfrequentie	Nieuwe reisfrequentie	Gebruik auto 'X'
Fulltime baan	Auto (100%)	0 min.	0€	4 keer per week	4	100%

*Gebruikskosten: Kosten per kilometer.
**Reiskosten: Kosten heen- en terugrit plus eventuele parkeerkosten. Verschil kosten is tussen auto 'X' en uw huidige vervoerswijze.
Huidige reiskosten zijn geschat op basis van uw opgaven voor reistijd en vervoerswijze.

Vorige Volgende

Figure 3.4: Questionnaire page containing a single experiment task

3.2.1 Section 1: Introductory text

The first page is aimed at making the respondent familiar with the purpose of the study and layout of the questionnaire. The translated version of the text used in the questionnaire is written below in italics. The term 'self-driving vehicle' is used instead of automated vehicle, because it is believed to appeal more to the imagination of people that are unfamiliar with AVs, than 'automated' or 'autonomous' vehicle.

'Dear respondent,

This questionnaire is about the (fictive) use of self-driving vehicles.

The purpose of this research is gain insight into the future consequences of automated driving, such as changes in transportation mode choice and travel frequency.

*The questionnaire consists of 4 parts and will take approximately **15 minutes** to complete.*

- *Firstly, travel behavior with regard to work/study (part 1) and shopping trips (part 2) will be considered*
- *Then, several questions will be asked while you are pretending to have access to a certain type of self-driving vehicle*
- *Finally, u will receive several questions regarding your personal characteristics.*

Your cooperation in this research is greatly appreciated! All answers will be treated confidently and anonymously.

Press 'start' to begin with the questionnaire.'

3.2.2 Section 2: Work / education context

The second part of the questionnaire will be used to determine the traveling context of work/education activities. This part also includes the only screen out possibility. A screen out is a redirect to a page that explains to the respondent that he or she is not eligible for this questionnaire. A screen out occurs on if the respondent does not practice any of the 4 suggested occupations (fulltime job/education and part-time job/education).

The maximum number of 'occupations' considered per respondent is 2. The routing of the questionnaire is programmed such that only 3 combinations of occupations are possible: fulltime job x par-time education, fulltime education x part-time job and part-time job x part-time education. It is also possible to continue the questionnaire with a single occupation. This leaves seven options to continue from, which can be seen in table 3.16.

Table 3.16: Possible combinations of occupations to continue from in the questionnaire
FT = fulltime
PT = part-time

Option #	FT job	FT education	PT job	PT education
1	✓			
2	✓			✓
3		✓		
4		✓	✓	
5			✓	
6			✓	✓
7				✓
0*				

*Leads to screen out

For each occupation selected by the respondent, the same questions will be asked regarding the travelling context. Only one destination is considered per occupation: The location where the respondent practices the occupation most often (not including their home). Some of these questions are 'dynamic', which indicates that they will only appear if a certain answer has been given to a previous question. For instance, the usage of a discount membership for public transportation will only be requested if the main transportation mode for trips to that job or education is ‘train’ or ‘bus/subway/tram’. The questioning follows a specific order which can be seen in figure 3.5. Each box in this figure that has a number represents a single question. Each question is used to make the respondent fill in a single variable. The variables pertaining to the questions of figure 3.5 and their answer categories can be seen in table 3.17.

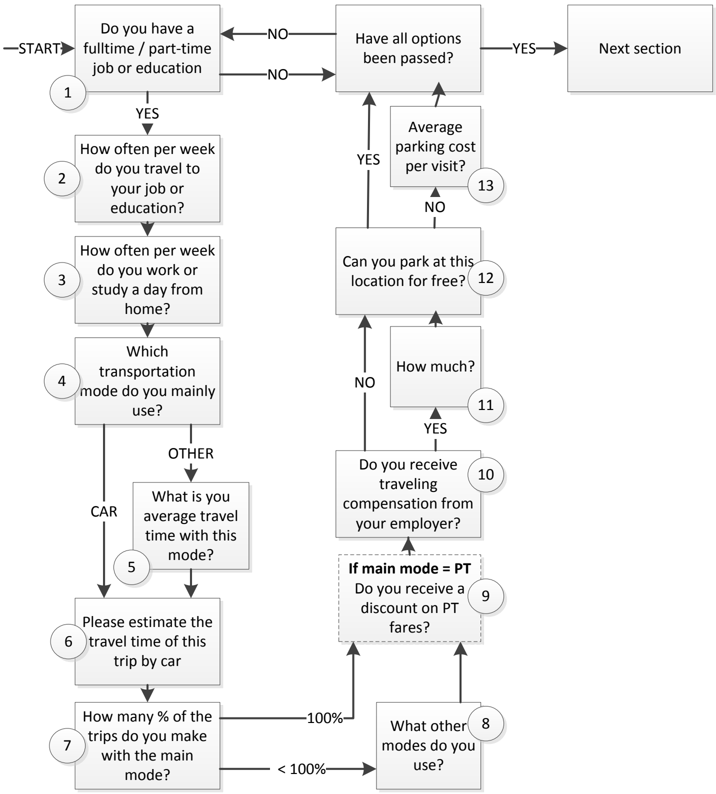


Figure 3.5 (above): Questions and routing of section 2 of the questionnaire

Table 3.17 (below): Variables and answer categories pertaining to the questions of section 2 of the questionnaire

#	Variable	Range
1	Has fulltime occupation	Fulltime job, fulltime education, none
	Occupation = part-time job	Yes, No
	Occupation = part-time education	Yes, No
2	Weekly travel frequency	0 -- 9 times
3	Weekly homeworking frequency	0 -- 9 days
4	Main transportation mode	Car, Train, Bus/subway/tram, Bike, Walk, Other, N.a.
5	Average trip duration with main mode	0 -- 999 minutes
6	Average trip duration with car	0 -- 999 minutes
7	Main mode usage rate	<50%, 60%, 70%, 80%, 90%, 100%, N.a.
8	Alternative transportation modes	Car, Train, Bus/subway/tram, Bike, Walk, Other
9	Usage of PT discount membership	No, 20% discount, 40% discount, 100% discount
10	Compensation for travel expenses	Yes, No
11	Compensated amount	100% compensated, 0 -- 99 cents per kilometer
12	Free or paid parking	Free, Paid, Unknown*
13	Average parking fee per visit	Unknown*, 0.00 -- 99.99 €

*If unknown is selected, a value will be estimated for parking expenses

3.2.3 Section 3: Driver's license and car ownership

The next section of the questionnaire is about driver's license and car ownership of the respondent. The routing of this page can be seen in image 3.6. Corresponding variables and answer categories can be seen in table 3.18. These questions are asked at a relatively early stage of the questionnaire, because car type is used in the experiment to calculate travel costs and therefore cannot be asked after the choice experiment. The list of car types to choose from is presented with images to increase clarity. Figure 3.7 is an image of this list as presented in the questionnaire.

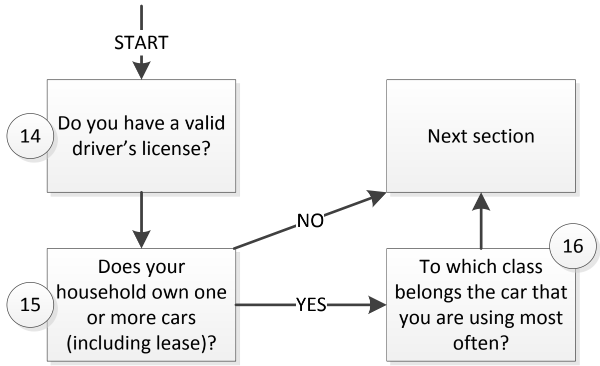


Figure 3.6 (above): Questions and routing of section 3 of the questionnaire

Table 3.18 (below): Variables and answer categories pertaining to the questions of section 3 of the questionnaire

#	Variable	Range
14	Has valid driver's license	Yes, No
15	Household owns (or leases) 1 or more cars	Yes, No
16	Class of most used car	Mini, Compact, Small-middle, Middle, Large-middle, Top class, N.a.

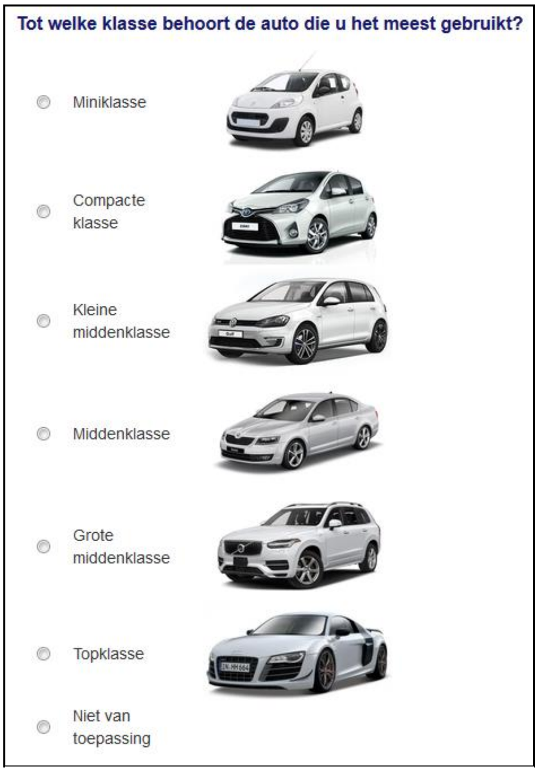


Figure 3.7: List of car classes as presented in the questionnaire

3.2.4 Section 4: Non-grocery shopping context

Before entering this section, a brief definition of 'shopping trips' within the context of this study will be presented to the respondent on a separate page in the questionnaire. This page reads (as translated from Dutch):

'Please read the following text before continuing the questionnaire.

The following questions are concerned with your shopping activities.
Shopping is defined in this questionnaire as:

'The making of non-daily purchases such as clothing, personal care products, domestic products etcetera.''

This section has the same purpose as, and is very similar to, the section about work-/study context. The routing of this section can be seen in image 3.8 and variables corresponding to the questions can be seen in table 3.19. The section begins with a brief explanation that the respondent must indicate at least 2, and a maximum of 3, shopping locations they visit on a regular basis, and that for each location they are required to indicate a self-recognizable name which will come back later in the questionnaire but will not be used for analyses. The differences in routing with section 2 (work/education context) are that the questions concerning compensation for trip expenses are not included and that a new question is included to identify the type of the shopping center.

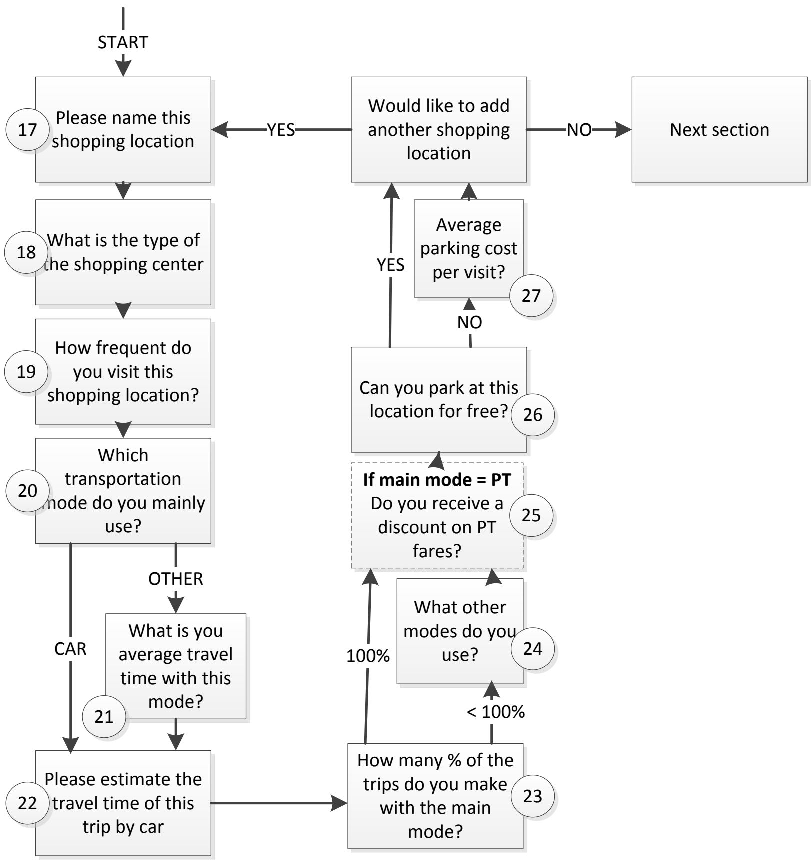


Figure 3.8: Questions and routing of section 4 of the questionnaire

Table 3.19: Variables and answer categories pertaining to the questions of section 4 of the questionnaire

#	Variable	Range
17	Name of shopping location	…
18	Shopping center type	City center, District c., Local c., Themed c., Other
19	Travel frequency	<1 x per half year, 1 x per half year, 1 x per 3 months, 1 x per month, 1 x per 2 weeks, 1 x per week, More than 1 x per week
20	Main transportation mode	Car, Train, Bus/subway/tram, Bike, Walk, Other
21	Average trip duration with main mode	0 -- 999 minutes
22	Average trip duration with car	0 -- 999 minutes
23	Main mode usage rate	<50%, 60%, 70%, 80%, 90%, 100%
24	Alternative transportation modes	Car, Train, Bus/subway/tram, Bike, Walk, Other
25	Usage of PT discount membership	No, 20% discount, 40% discount, 100% discount
26	Free or paid parking	Free, Paid, Unknown*
27	Average parking fee per visit	Unknown*, 0.00 -- 99.99 €

*If unknown is selected, a value will be estimated for parking expenses (refer to table 3.6)

3.2.5 Section 5: Stated choice experiment

The section covering the stated choice experiment consists of 6 questionnaire pages: An introduction to automated driving, a page where the respondent can decide whether or not to add an additional shopping location which they would consider visiting if they had an AV, a trial of the choice task and three actual choice tasks. The contents and layout of these pages are discussed in chapter 3.1.6.

The tables featured in each choice task page have been formatted, and questions have been formulated correctly, according to the number of destinations and types of occupations indicated by the respondent. In total, 14 different formats have been created to cover all combinations of occupations chosen and amounts of shopping locations indicated. Based on the respondents' answers during the questionnaire, they will be redirected after the trial to one of 14 sub-questionnaires with the correct stated choice experiment. This routing is visible in figure 3.9. The decision whether or not to add the third shopping location in section 4 has not been included in the routing, because this would require the creation of 14 additional sub-questionnaires which would take too much effort. Instead, if a respondent has indicated only 2 shopping locations in section 4, the third row of the 'shopping location-table' will remain empty.

3.2.6 Section 6: Socio-demographics

This section covers the socio-demographic characteristics of the respondent. Table 3.20 shows the variables pertaining to the questions of this section and their answer categories. 'Income' has been identified in the literature analysis as a relevant explanatory variable but will not be included to respect the privacy of respondents. Instead, 'highest completed education' has been chosen because of the correlation between these two concepts. At some point, respondents are asked whether they live in a students' residence. If the answer to this question is yes, they do not have to answer their household size, because the number of household member is expected to be irrelevant for this group within the context of this study.

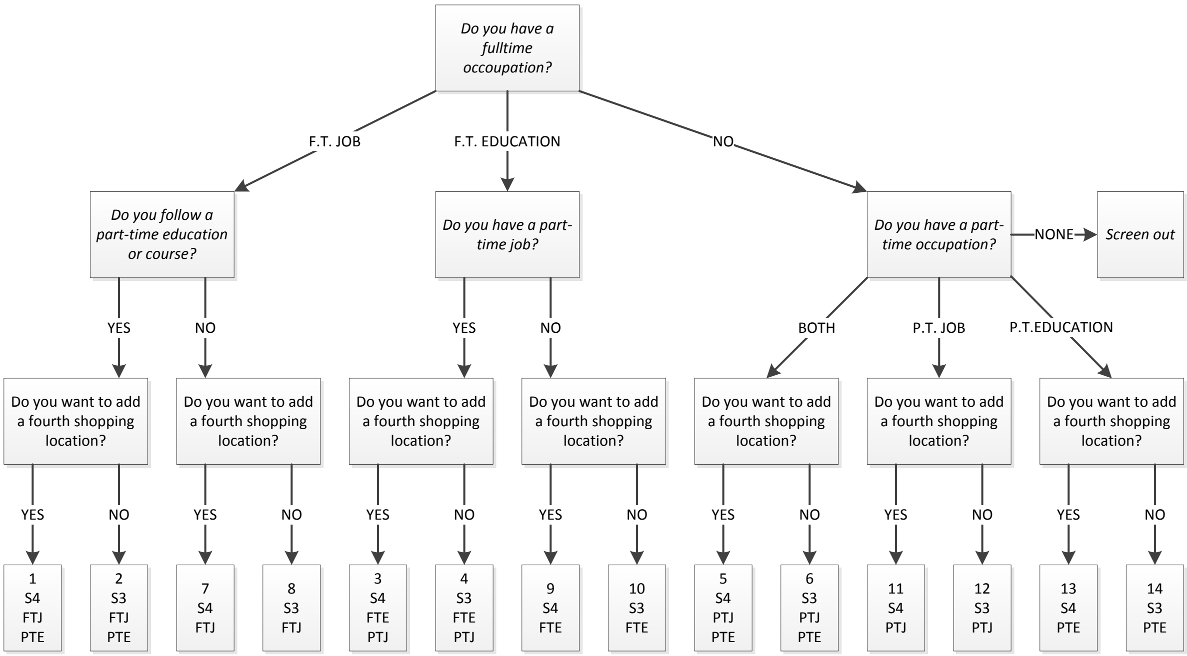


Image 3.9: Global questionnaire routing
S4 = Extra shopping location added after introduction of AV, S3 = No extra shopping location added
FTJ = Fulltime job, FTE = Fulltime education, PTJ = Part-time job, PTE = Part-time education

Table 3.20: Variables and answer categories pertaining to the questions of section 6 of the questionnaire

Variable	Range
Age category	<20, 20-30, 30-40, 50-65, 65+ years old
Sex	Male, female
Highest completed education	None/primary school, VMBO, HAVO/VWO, MBO, HBO, WO, Other
Home = student residence	Yes, No
Houshold size	1 -- 9 persons
4 digits of postal code	0000 -- 9999
Neighborhood type	Highly urban, moderately urban, sub-urban, rural

3.2.7 Section 7: Concluding remarks

In the final page, respondents are thanked for their participation and are given the opportunity to make remarks. The remarks filled in by respondents can be read in appendix 2.

3.2.8 Population and approaching respondents

The population targeted in this sample are Dutch citizens. To reach potential respondents, e-mail invitations have been sent to family, acquaintances, 2nd degree acquaintances, colleagues and students from classes related to this subject. Furthermore, an agreement was made with the Netherlands Institute for Transport Policy Analysis (KiM) for the involvement of a Dutch market panel (PanelClix). The members of this panel were selected based on their gender and age to compensate for statistical deviations from the national average, resulting from the earlier collected ‘convenience sample’.

3.3 Analysis approach

This chapter will discuss how the results obtained with the questionnaire will be analyzed. The purpose of this study is bilateral: It aims to investigate the influence of automated driving on travel demand, and to find which factors determine this impact. For the former purpose, several calculations must be made using the output of response variables. For the latter purpose, an ordinal regression model will be estimated using the factors as explanatory variables. The following two sections will discuss these procedures.

3.3.1 Calculating the impact on travel demand

The impact on travel demand will be represented by changes in: Transportation mode usage (modal shares), weekly trip frequency and average trip length (the dependent variables). The analyses will be separated per trip motive. The calculation of each of these the dependent variables will be discussed consecutively in this chapter.

Transportation mode usage

The first (set of) dependent variable(s) is concerned with the change in transportation mode choice. Transportation mode usage is represented as a number of variables that indicate the usage percentage of each transportation mode. The sum of all these variables is 100%.

Difference in transportation mode usage will be analyzed by comparing weighted modal shares per destination from before and after the introduction of the AV. The modal shares are weighted based on the travel frequency for each destination. The modal shares for a single destination, for a single respondent are calculated as follows:

Step 1: For a certain destination, the respondent must select their currently main transportation mode out of the following list (section 2 or 4 of the questionnaire):

Table 3.21: Transportation mode answer categories

List of transportation modes
Car
Train
Bus / subway / tram
Bycicle
Walking
Other, namely …

Step 2: They must then indicate for which percentage of the trips (to a certain destination), they are using this main transportation mode. A percentage can be chosen between 100% and 50%

Step 3: If the usage percentage of the main transportation mode isn't 100%, they must indicate which alternative transportation modes they are using. They can pick multiple alternative modes from a list of Booleans in the questionnaire, each representing one of the transportation modes from the list in table 3.21.

Step 4: The usage percentages of alternative transportation modes is calculated by dividing the remaining percentage after deduction from the main transportation mode usage percentage, with the number of alternative modes used, and assigning this percentage to each of the alternative modes used. For example: If the main transportation mode is car with a usage percentage of 70% and alternative modes are bus and bicycle, the resulting modal shares for trips to the concerning destination are:

Table 3.22: Example of modal share calculation

Mode	Car	Bus/subway/tram	Bycicle
Share	70%	15%	15%

This procedure assumes that the usage percentages of all alternative transportation modes is equal, although this does not have to be the case. The assumption might lead to minor misconceptions in the calculation of modal shares. This is however not expected to cause major discrepancies, because this assumption only comes into practice if 3 or more different transportation modes are used to travel to a single destination, which rarely occurs.

Step 5: Respondents must indicate in the choice experiment which percentage of trips to a certain destination they would make with the AV: 'The usage percentage of the AV'. This response variable was preferred over a response variable such as: 'The new usage percentage with main transportation mode', because it is more straightforward and provides more accurate information about the usage of AVs.

Step 6: In order to calculate the 'new' modal shares, after gaining access to an AV, the assumption is made that the usage percentage of the AV will lead to an equally proportional decline of the usage percentages of all formerly used transportation modes that are not the same as the AV. A private AV is considered the same transportation mode as cars, but an autonomous taxi AV is considered a unique transportation mode. 2 examples of calculations of new modal shares can be seen in table group 3.23. The highlighted parts represent variables filled in by the respondent for usage percentage. In example 1, the AV is a private car, in example 2 the AV is an autonomous taxi.

Table group 3.23: Example of modal share calculation after gaining access to an AV

CURRENT	Main mode	Alternative modes	
Mode	Car	Bus +	Bycicle
Share	70%	15%	15%

NEW 1	(private) AV	Alternative modes	
Mode	Car	Bus +	Bycicle
Share	80%	10%	10%

NEW 2	(taxi) AV	Alternative modes		
Mode	Taxi	Car	Bus +	Bycicle
Share	80%	14%	3%	3%

It has happened in the questionnaire that respondents have filled in a lower value than 100% for AV usage percentage (private AV), while they currently use car 100% of the time. Therefore, the usage rate of ‘cars’ drops to for example 80%, but it is unknown to which transportation mode the remaining 20% should be attributed. To solve this issue it has been assumed that car usage cannot decline as a result of lower private AV usage rate. This assumption makes sense, because the automated driving systems of AVs can simply be turned off if they are not desired, and therefore no reason has been given to use the car less.

Another issue that occurred when analyzing the results is that some individuals did not check any of the Booleans for alternative transportation modes, while their indicated usage rate of the main transportation mode was below 100%. The remaining % of trips have in these cases been attributed to the transportation mode category ‘unknown’.

Step 7: Aggregated (weighted) modal shares from before and after the introduction of the AV are calculated by multiplying the modal shares for each destination with their travel frequency, and adding the resulting values. The difference in usage of separate transportation modes is calculated by dividing the new modal shares by the current modal shares. This value is preferred over subtracting the current from the new modal shares, because it is independent of the height of the current usage rate.

Travel frequency
The calculation of travel frequency difference is very straightforward, as the respondent has to fill in current and new travel frequency, which can be subtracted from each other. For non-grocery shopping destinations, travel frequency answers (such as ‘once per month’) will first be converted to the equivalent weekly frequency.

Average trip length
Trip length, within the context of this study, is independent of transportation mode choice or situational factors. It is represented by the response variable ‘the one-way, door-to-door, average travel time per car’, which respondents must state for all destinations, regardless of transportation mode used. The average trip length for non-grocery shopping activities is calculated by multiplying the travel time per car and travel frequency of each shopping location, and then dividing the sum of those values by the sum of all travel frequencies. Table 3.24 is an example of such a calculation.

Table 3.24: Example of average trip length calculation

	Travel time		Frequency		Time*Freq
Location 1	30	x	0.5	=	15
Location 2	20	x	1	=	20
Location 3	10	x	2	=	20
Location 4	40	x	0	=	0
			+		+
Total			3.5		55
Average trip length			55 / 3.5	=	**15.7**

3.3.2 Identifying relevant factors

In order to identify factors that are related to the impact of automated driving on travel demand, the ordinal regression model is used. This model is suitable for analyzing the relationship between an ordinal scale dependent variable and multiple dichotomous and/or interval scale explanatory variables.

Ordinal regression is basically a series of binary logistic regressions, comparing first the lowest ordinal category versus the other categories, then the two lowest categories versus the rest, then the three lowest categories etcetera, until in the last logistic regression the highest category is compared to all other classes (UK National Center for Research Methods, 2011). The result is a single linear regression function and a number of threshold parameters that are determined by each binary logistic regression. The probability of an outcome is the probability that the estimated function plus a random error lies within the range of the two threshold parameters that demarcate that outcome:

$$P_{ni} = P(k_{i-1} < \sum_{j=1}^{J} \beta_j X_{nj} + \varepsilon \leq k_i)$$

Where
P_{ni} = the chance of outcome i for case n
k_i = upper threshold parameter for outcome i
J = the number of explanatory variables
β_j = the estimated parameter of explanatory variable j
X_{nj} = the value of case n for explanatory variable j
ε = random error

There are i-1 threshold parameters for i ordinal categories. This is because the lower threshold parameter demarcating the lowest ordinal category is $-\infty$ and the highest threshold parameter demarcating the highest ordinal category is $+\infty$.

To test whether the model has significant predictive power, the log-likelihood of the estimated model is compared to that of the 'intercept only' model, which has estimated threshold parameters but no explanatory variables. Log-likelihood is calculated for each model as follows:

$$LL = \sum_{n=1}^{N} \sum_{i=1}^{I} X_{ni} \cdot ln(P_{ni})$$

Where
LL = the log-likelihood ratio
N = the sample size
I = the number of ordinal categories
X_{ni} = a binary that reports 1 if the outcome of case n is ordinal category i, and 0 otherwise
P_{ni} = the model's estimated probability of case n leading to outcome i

This function essentially assigns 'penalty-points' to the model for being off with their predictions; An outcome that had only a low estimated probability will add more negative value to the LL than an outcome that had a high probability. The ‘intercept-only’ model has fixed probabilities for each ordinal category outcome because there are no explanatory variables included, so the comparison between the intercept-only model and estimated model checks whether the explanatory variables in the estimated model significantly improve the predictive power of the model. To test whether there is an actual improvement, a Chi-squared test is done using the LL of both models. The significance level of this test shows whether the LL are statistically different, meaning there is an improvement.

In order to measure the predictive power of the model, McFaddens pseudo-R^2 can be calculated as follows:

$$R^2 = 1 - \frac{LL_M}{LL_B}$$

Where
LL_M = the log-likelihood of the estimated model
LL_B = the log-likelihood of the base model

The resulting value is a value between 0 and 1, representing the predictive power of the explanatory variables in the estimated model. There is much debate about what value of R^2 represents decent predictive power. It can be stated however stat the R^2 should be over 0.10 to be ‘adequate’ (Falk & Miller, 1992)

The following 8 models will be estimated with NLOGIT/LIMDEP software to identify factors related to change in travel demand:

- 2 ordered regression models (one for work/education and one for shopping trips) with dependent variable (DV): AV usage rate;
- 1 ordered regression model (for work/education) with DV : Change in usage of public transportation;
- 2 ordered regression models with DV: Change in usage of bicycle;
- 2 ordered regression models with DV: Change in travel frequency;
- 1 ordered regression models (only for shopping trips) with DV: Change in average trip length.

For the models concerned with a change in transportation mode, only cases have been selected in which this transportation mode is used as a main or alternative transportation mode. ‘Panel effects’, which occur when multiple records in the dataset belong to the same respondent causing heterogeneity, have been accounted for in all models with the ‘;panel’-function of NLOGIT.

In order to achieve an ‘optimal’ model estimation with only the attributes and significant variables, a stepwise procedure was followed of reducing the most insignificant variables from the full model, until all remaining variables were significant ($p<0.05$). The full model estimations of all models can be viewed in appendix 4 to 11. The models will not include interaction variables, because the inclusion of these variables in the models lead to a large and uneasy to understand number of significant variables.

4 Results

In this chapter the following topics are discussed consecutively: Firstly the preparation of questionnaire data for analysis, secondly a description of the sample and context, thirdly the resulting changes in travel demand and fourth the factors that influence those changes in travel demand. The concluding section of this chapter summarizes the most important findings from the analysis.

4.1 Data preparation

In order to perform analyses on the data obtained with the questionnaire, the data must be formatted appropriately to be compatible with the software used for the analysis. Furthermore, the data must be 'cleaned' in order to prevent bias from extreme values. This section discusses the procedure followed for preparing the data, stepwise.

Step 1: Dataset creation

Firstly, an initial dataset has been created by merging all cases from the sub-questionnaires with the main questionnaire into a single excel-file, with the respondent ID as keyed variable. Each case in this dataset represents a single choice task filled in by an individual. Therefore, there are three cases per respondent included in the dataset. Table 4.1 gives an impression of this format. To make the dataset suitable for analysis, this initial dataset was then reformatted such that each case represents a single choice task for single destination for an individual. This conversion was done within Excel. Table 4.2 gives an impression of the resulting dataset.

Table 4.1: Initial dataset schematic

Case ID		**Experiment**			**Context**						**Sociodem.**	
			Dest. 1	**Dest. 2**	**Destination 1**			**Destination 2**				
Resp. ID	**Task**	Attributes	Response	Response	Mode	Tr. Time	Etc.	Mode	Tr. Time	Etc.	Age	Etc.
24515	**1**											
24515	**2**											
24515	**3**											

Table 4.2: Converted dataset schematic

Case ID			**Experiment**		**Context**				**Sociodemographic**		
Resp. ID	**Task**	**Destination**	Attributes	Response	Mode	Tr. Time	Park cost	Etc.	Age	Sex	Etc.
24515	**1**	**Destination 1**									
24515	**1**	**Destination 2**									
24515	**2**	**Destination 1**									
24515	**2**	**Destination 2**									
24515	**3**	**Destination 1**									
24515	**3**	**Destination 2**									

Step 2: Recoding variables

Several variables have been recoded to make them operational for the analysis software. String variables that represent a quantity, such as 'Trip frequency' or 'Main transportation usage percentage' were converted from texts such as 'Once a week' or 'Less than 50%' to numerical values. All categorical variables, including context characteristics, socio-demographic characteristics and AV attributes, have been recoded into dichotomous variables following the principle of dummy coding. Some answer categories, such as 'Age 50-64' and 'Age 65+' were merged, in order to create larger and more significant groups.

Step 3: Computing dependent variables

Several new variables have been computed using Excel formulas to represent the dependent variables: Change in transportation mode use, change in travel frequency and change in average trip length. The corresponding calculations per variable have been discussed in chapter 3.3.1.

Step 4: Dealing with missing values

Missing values are variables that have not been filled in by a respondent. Firstly, the response variables have been checked for missing values, because cases with missing response values cannot be used for analysis. The 'panel'-sample (N=533) provided only completely finished questionnaires, meaning there are no missing values at all. Some respondents from the 'convenience'-sample (N=216) however quit the questionnaire before finishing. This resulted in several cases with missing values for one or both response variables. To deal with this, two copies of the dataset were created named 'Transportation mode choice-dataset' and 'Travel frequency-dataset'. In the first copied dataset, all cases with missing values for the response variable 'AV usage percentage' were deleted from the dataset, and in the second copied dataset cases with missing values for the response variable 'Travel frequency' were deleted.

As for the explanatory variables, there are no missing values left because in the questionnaire used for the 'convenience'-sample, the questions related to socio-demographic characteristics came before the stated choice experiment.

Step 5: Dealing with outliers

If respondents use extreme and unrealistic values, this can influence the average for that variable considerably. Therefore it is wise to deal with these values to prevent a bias in the results. In the questionnaire, most variables were categorical scale and therefore cannot have outliers. However, several interval-type variables have been manipulated as follows.

- 14% of cases indicated a drop in weekly travel frequency to work or education destinations due to the AV of more than 2. There is no logical reason to support this kind of decline in travel frequency and it is therefore believed that many of these people did not read the corresponding question well, and thought they had to reply their 'Travel frequency with the AV' instead of 'Total travel frequency'. Cases with a travel frequency decline of more than 2 times per week have been removed from the travel frequency-dataset as well as two cases that indicated an increase in travel frequency of respectively 8 and 9 times per week.

- There were a handful of extreme outliers within the variables 'Travel time with main mode', 'Travel time per car', 'Estimated trip cost', 'Expected difference in travel time with AV' and

‘Expected difference in travel cost with AV’. Therefore, thresholds have been determined for the maximum and minimum values of these variables. Values that exceed these thresholds have been set to threshold value. The following maxima and minima have been determined for each of the variables:

- ‘Travel time with main mode’: max. 200 minutes;
- ‘Travel time per car’: max. 200 minutes;
- ‘Estimated trip cost’: max. 100 euros;
- ‘Expected difference in travel time with AV’: max. +50 minutes, min. -50 minutes;
- ‘Expected difference in travel cost with AV’: min. -50 minutes.

STEP 6: CONVERTING DEPENDENT VARIABLES TO ORDINAL SCALE

Figure 4.1 and 4.2 show the distribution of the two response variables. Clearly, the different ordinal categories of these variables have a very uneven number of cases. If the number of cases within an ordinal category is too low, this may lead too insignificant results and lower performance of statistical model estimations. Therefore, some of the underrepresented ordinal categories of the dependent variables that are derived from these response variables have been merged. The resulting categories per dependent variable can be seen in table group 4.3.

STEP 7: REMOVING HIGHLY CORRELATING EXPLANATORY VARIABLES

If a number of explanatory variables are highly correlated to each other, their capability of predicting the value of the dependent variable will overlap and so their unique contributions to the model fit will be very low. If n explanatory variables are highly correlated to each other, n-1 of these variables are redundant and should be removed from the analysis. A number of correlation matrices were generated with SPSS to identify cases of collinearity between the explanatory variables of this study.

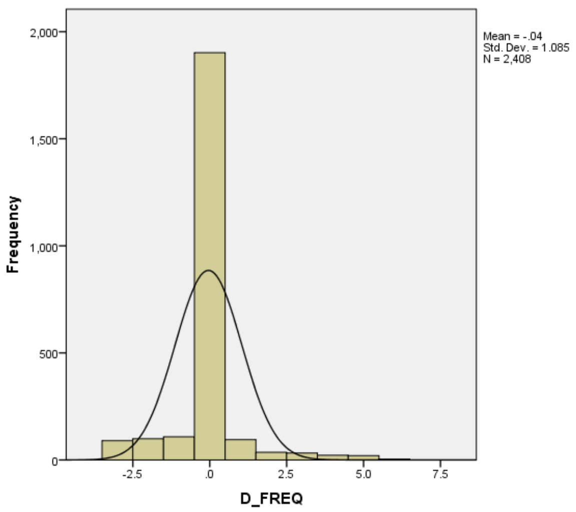


Figure 4.1: Distribution response variable ‘Travel frequency’

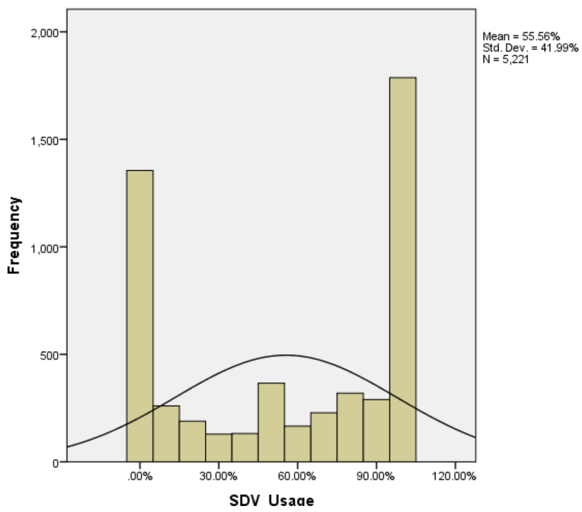


Figure 4.2: Distribution response variable ‘Automated vehicle usage percentage’

Table group 4.3: Ordinal categories per dependent variable

AV usage rate	
Category	**Description**
1	0% usage rate
2	10-30% usage rate
3	40-60% usage rate
4	70-90% usage rate
5	100% usage rate

Change in travel frequency	
Category	**Description**
1	Decreased travel frequency
2	Same travl frequency
3	Increased travel frequency

Change in [transportation mode] usage	
Category	**Description**
1	100% decline in usage
2	Partial decline in usage rate
3	Same usage rate

Change in average shopping trip length	
Category	**Description**
1	Decreased average trip length
2	Same average trip length
3	Increased average trip length

Pearson's correlation values of over 0.5 occurred between the following explanatory variables:

- 'Travel duration with main transportation mode', 'Estimated trip cost' and 'Estimated travel duration per car'. Only 'Estimated travel time per car' has been included in the ordinal regression models, because this variable is not dependent on transportation mode used and can be used best as an indicator for trip length.

- 'Age under 30', 'Following a fulltime education' and 'Living in a students' residence' are also highly correlated to each other. Only 'Age under 30' has been included in the models because this personal information is most accessible.

4.2 Sample and context characteristics

Table group 4.4 shows a number of tables indicating the characteristics of the sample of N=749. Some characteristics can be compared to Dutch national averages. In spite of the efforts made to create a representative sample for the Dutch population, there are some small deviations from the national average for the characteristics: Sex, age group and household size. Somewhat underrepresented groups are: Females (39%), age 18-29 (13%), age 50 plus (34%) and household size 1 or 2 (47%). It can be concluded that the sample is an approximation of the Dutch population but not completely representative.

Approximately 19% of the respondents do not have a driver's license, but only 14% never uses a car. This indicates that some respondents may be travelling per car as passengers. The majority of respondents have followed higher education (63%). This can be explained by the fact that the convenience-sample of N=216 featured a large portion of university students. Most respondents have a fulltime job (76%), while only a small percentage of the total is fulltime student (10%). A small percentage of respondents indicate that they have a large middle class or top class car (12%). The most frequenctly selected residential area type are the sub-urbs (39%), while the least chosen residential area is 'central and highly urbanized' (13%).

Table group 4.4: Sample characteristics. Dutch averages source: CBS 2016 / CBS 2017

Panel member	
Yes	216 (29%)
No	533 (71%)

Sex		Dutch avg.
Male	61%	50%
Female	39%	50%

Age group		Dutch avg.
18 to 29	13%	18%
30 to 39	28%	15%
40 to 49	26%	17%
50 and older	34%	50%

Household car possesion		Dutch avg.
Yes	86%	72%
No	14%	28%

Household type		Dutch avg.
Student residence	5%	
HH Size = 1 or 2	47%	70%
HH Size = 3 or more	48%	30%

Driver's license possesion	
Yes	81%
No	19%

Highest completed education	
Lower*	37%
Higher**	63%

*No education, primary school, VMBO, MBO

**HAVO, VWO, HBO, University

Has a fulltime job	
Yes	76%
No	24%

Has a fulltime education	
Yes	10%
No	90%

Most used car	
None	14%
Mini/compact class	24%
Small middle class	22%
Middle class	28%
Large middle/top class	12%

Living environment	
Highly urban	13%
Moderately urban	28%
Sub-urban	39%
Rural	20%

The travel context characteristics can be subdivided into those pertaining to work- / educational destinations, and those pertaining to non-grocery shopping destinations. These will be reviewed in the following sections.

Work and education context

The average weekly travel frequency to a work or education destination is 3.5 on average, with an estimated one-way travel duration of 29 minutes. If all travel would be per car, average travel duration would be 27 minutes. The average estimated trip cost (two-way) after compensation is €3.24. It is possible that the estimated trip cost for a certain trip is negative, if travel compensation per kilometer for that trip exceeds travel expenses per kilometer. On average, respondents work or study 1 day per week from home (See table 4.3). The most used transportation mode for trips to work or educational facilities is the car (55%), followed by the bicycle (22%). These modal shares are not weighted by the travel frequency to each destination. 8% of the trips are made with unknown transportation modes, because respondents failed to select alternative transportation modes after stating the usage percentage of their main transportation mode was below 100% (See table 4.4).

Table 4.3: Average work / education context characteristics

	Weekly travel frequency	Estimated travel cost	Travel time with main mode	Estimated travel time per car	Days per week teleworking
Mean	3.53	€3.24	29.34 min.	27.03 min.	0.99
Std. dev.	1.78	9.82	23.07	22.91	1.43
Minimum	0.00	-56.95	0.00	0.00	0.00
Maximum	9.00	100.00	200.00	200.00	9.00

Table 4.4: Average modal share for trip to work/educational facilities, per respondent

Transportation mode used for work and education travel	
Car	55%
Train	9%
Bus/subway/metro	4%
Bycicle	22%
Walking	1%
Other	1%
Unknown	8%

Non-grocery shopping context

The average number of visits to the shopping destinations is 0.6 times weekly, with an average one-way travel duration of 18 minutes. If all travel would be per car, average travel duration would still be approximately 18 minutes. The estimated average trip cost (two-way) including parking fees €7.08 (See table 4.5). The type of shopping center visited most often for non-grocery shopping is the city center (40%), followed by local (32%) and district (30%) centers (See table 4.6). The most used transportation mode for non-grocery shopping trips is the car (51%), followed by the bicycle (22%). The train is used considerably less frequently for these shopping trips than for commute, while people are walking much more often in comparison. This has likely to do with the shorter average travel distance (See table 4.7).

Table 4.5: Average non-grocery shopping context characteristics

Variable	Weekly travel frequency	Estimated travel cost	Travel time with main mode	Travel time by car
Mean	0.60	€7.08	18.41 minutes	17.52 minutes
Std. dev.	0.64	12.12	19.70	19.95
Minimum	0.00	0.00	0.00	0.00
Maximum	2.00	100.00	200.00	200.00

Table 4.6: Shopping center types used for non-grocery shopping

Shopping center type	
Themed center	13%
City center	40%
District center	30%
Local center	32%

Table 4.7: Average modal share for trip to work / educational facilities, per respondent

Transportation mode used	
Car	51%
Train	4%
Bus/subway/metro	5%
Bycicle	22%
Walking	8%
Other	1%
Unknown	9%

4.3 The impact of automated driving on travel demand

Using travel context characteristics and the outcome of the response variables, the impact of AVs on travel demand was calculated in terms of changes in modal shares, travel frequency and average shopping trip length. These calculation procedures are described in chapter 3.3.1. The impacts on work/education travel and non-grocery shopping travel have been analyzed separately and will be discussed separately in the following two sections. Changes in transportation mode choice will be discussed for two scenarios: One in which all respondents have access to autonomous taxis, and one in which each respondent owns either a LVL 3/4 or LVL 5 AV. It should be noted that no significant difference was found between the effects of a LVL 3/4 and LVL 5 AV on travel demand, and that their results are therefore discussed simultaneously. For practical reasons, these scenarios will further on be referred to as 'AV ownership scenario' and 'Automated taxi scenario'.

4.3.1 Trip motive: work and education

Table 4.8, and figure 4.3 and 4.4 respectively show the current modal shares for work/education travel and those in case of the AV ownership scenario. There are some drastic effects noticeable that AV ownership can have on these modal shares. Firstly, the usage of cars is expected to increase by 21%, leading to a 21% increase in car VHT for work/education travel. Public transportation (PT) and 'other' modes are declining the most, with 45% (train), 52% (bus/subway/tram) and 70% (other). Since most respondents do own a driver's license and car, this could imply that they would use the AV more often than their current car because they value the ability to be productive/entertained while travelling highly. Active transportation modes are also expected to decline considerably, by 24% (bicycle) and 22% (walking), implying that even for short distance travel, AVs are an attractive transportation mode.

Table 4.8: Current modal shares, modal shares in case of AV ownership scenario and difference in transportation mode usage for work/education commute

Transportation mode	Current share	New share	Difference
Car	60.8%	73.9%	+21%
Train	8.1%	4.5%	-45%
Bus/subway/tram	4.6%	2.2%	-52%
Bycicle	22.6%	16.6%	-24%
Walking	1.1%	0.8%	-22%
Other	0.5%	0.1%	-70%
Unknown	3.6%	1.9%	-47%

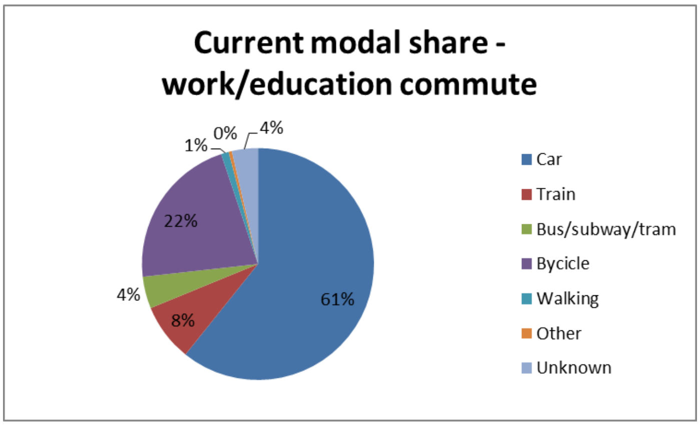


Figure 4.3: Current modal share for work/education trips

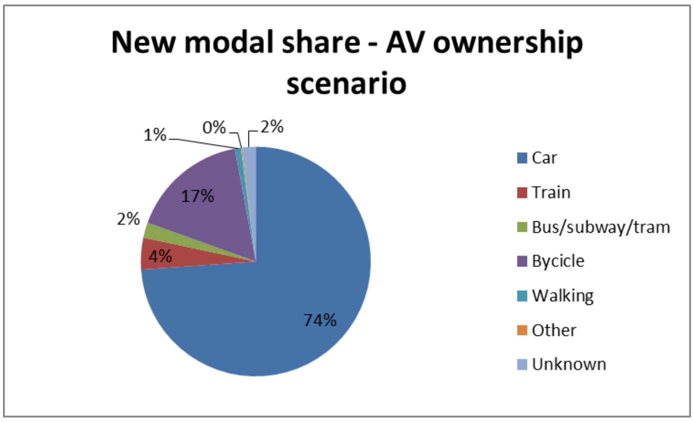
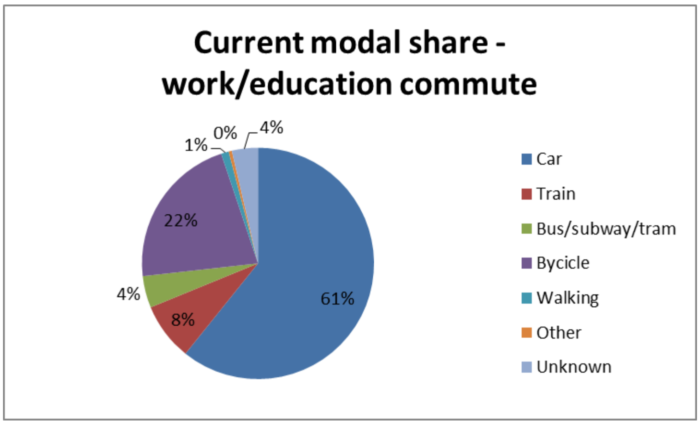


Figure 4.3: Modal share in 'AV ownership scenario' for work/education trips

Table 4.9, and figure 4.4 and 4.5 show the same kind of statistics but for the autonomous taxi scenario. A rather surprising effect is that many car users would give up travelling with their private car to use autonomous taxis instead. This results in a large decline of private car usage by 64% and a modal share of autonomous taxis of 53% for work/education travel. The result is an increase in car VHT (private car and autonomous taxi combined) for work/education of 23%, not including unmanned VHT. Declining usage of PT and active transportation modes are rather similar in this scenario compared to the AV ownership scenario: -40% (train), -67% (bus/subway/tram), -27% (bicycle) and -24% (walking).

Table 4.9: Current modal shares, modal shares in case of autonomous taxi scenario and difference in transportation mode usage for work/education travel

Transportation mode	Current share	New share	Difference
Car	61.0%	21.9%	-64%
Autonomous taxi		53.3%	
Train	8.0%	4.8%	-40%
Bus/subway/tram	4.4%	1.9%	-57%
Bycicle	21.5%	15.8%	-27%
Walking	1.1%	0.8%	-24%
Other	0.5%	0.1%	-75%
Unknown	3.6%	1.5%	-59%



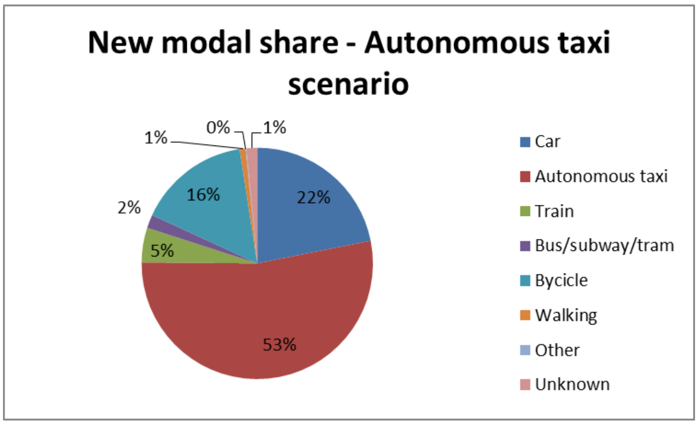


Figure 4.4: Current modal share for work/education travel

Figure 4.5: Modal share in 'Autonomous taxi scenario' for work/education travel

Table 4.10 shows the change in travel frequency per work/education destination as a result of gaining access to either an autonomous taxi or private AV. It appears that for most destinations (79%), the respondents do not change their travel frequency. This is not very surprising, as a lot of people probably cannot decide whether or not to visit their work location more or less often. 12% of the work/education destinations, respondents would visit less often. This could be because they predict to be able to finish more work while travelling per AV, enabling them to take a day off. However, it is also plausible that a decline in travel frequency is caused because some of the respondents did not fully understand how to fill in the response variable regarding the 'new' travel frequency. They might have misinterpreted it as 'Travel frequency with the AV' instead of 'Total travel frequency', causing some bias. 9% destinations would be visited more often if an AV can be used, likely because they make travelling less unattractive, inducing more trips.

Table 4.10: Change in travel frequency per destination due to owning an AV or being able to use an autonomous taxi, for work/education travel

Change in travel frequency due to AV	
Lower frequency	12%
Same frequency	79%
Higher frequency	9%

4.3.2 Trip motive: non-grocery shopping

Table 4.11, and figure 4.6 and 4.7 respectively show the current modal shares for non-grocery shopping travel and those in case of the AV ownership scenario. Car usage is expected to increase by 37% in this scenario, leading to a 24% increase in car VHT. Similarly to work/education travel, public transportation usage is expected to decline the most, by 42% (train) and 53% (bus/subway/tram), but also active transportation modes are expected to decline substantially, with 29% (bicycle and walking). It is striking that quite a large share of respondents would give up walking or cycling in favor of transportation with a private AV for shopping travel, even more than for work/education travel. A reason for this could be that with the AV, bought products can be transported more conveniently and in larger quantities than per bike or walking.

Table 4.11: Current modal shares, modal shares in case of AV ownership scenario and difference in transportation mode usage for non-grocery shopping travel

Transportation mode	Current share	New share	Difference
Car	45.6%	62.5%	+37%
Train	1.2%	0.7%	-42%
Bus/subway/tram	3.4%	1.6%	-53%
Bycicle	29.6%	21.2%	-29%
Walking	15.8%	11.2%	-29%
Other	0.8%	0.6%	-32%
Unknown	3.5%	2.3%	-34%

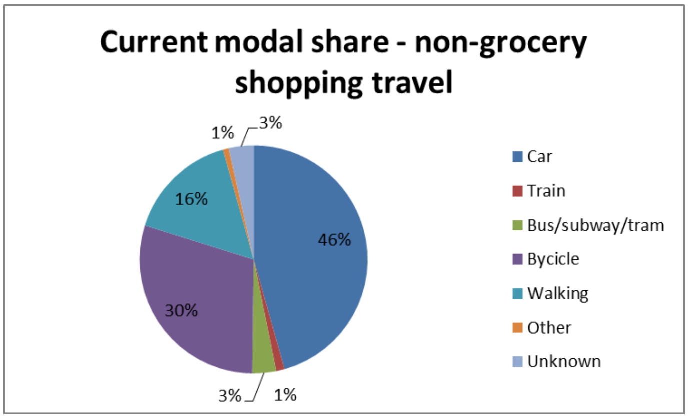


Figure 4.6: Current modal share for non-grocery shopping travel

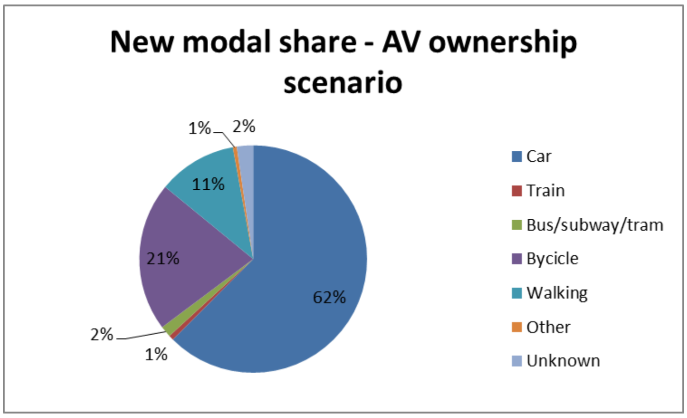


Figure 4.7: Modal share in 'AV ownership scenario' for non-grocery shopping travel

Table 4.12, and figure 4.8 and 4.10 respectively show the current modal shares for non-grocery shopping travel and those in case of the autonomous taxi scenario. Similarly to work/education travel, private car usage is expected to decline drastically (-64%) in favor of the autonomous taxi (47% usage percentage). It therefore appears that autonomous taxis are considered a very attractive transportation mode for both work/education and shopping travel. The combined VHT of private cars and autonomous taxis for non-grocery shopping travel would increase by 25% in this scenario. The decline percentages of all other transportation modes are very similar to those in the AV ownership scenario: -41% (train), -52% (bus/subway/tram), -29% (bicycle) and -30% (walking).

Table 4.12: Current modal shares, modal shares in case of autonomous taxi scenario and difference in transportation mode usage for non-grocery shopping travel

	Current	New	Difference
Car	45.4%	16.1%	-64%
Autonomous taxi		46.8%	
Train	1.2%	0.7%	-41%
Bus/subway/tram	3.5%	1.7%	-52%
Bycicle	29.7%	21.0%	-29%
Walking	15.8%	11.1%	-30%
Other	0.8%	0.6%	-31%
Unknown	3.6%	2.0%	-44%

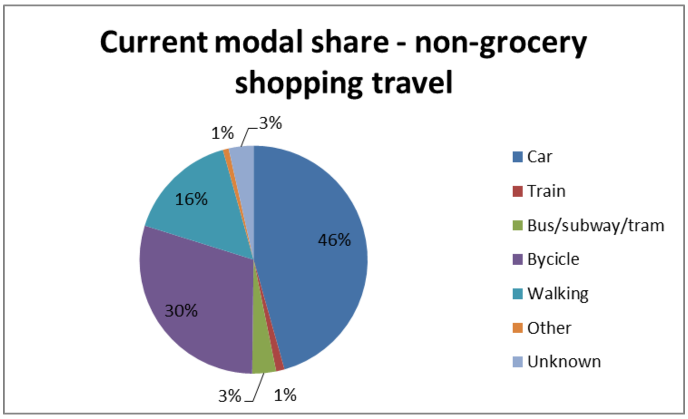


Figure 4.8: Current modal share for non-grocery shopping travel

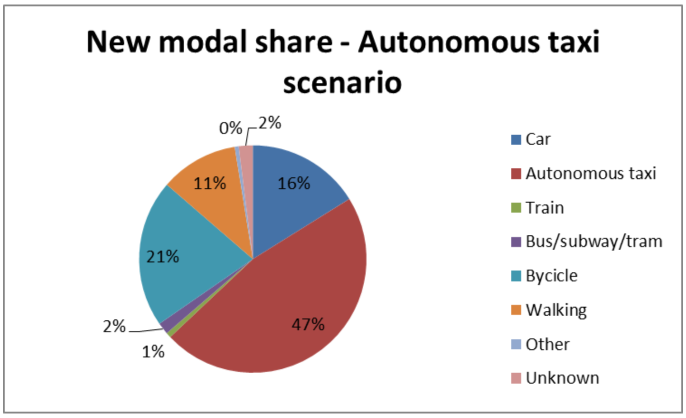


Figure 4.10: Modal share in 'Autonomous taxi scenario' for non-grocery shopping travel

Table 4.13 shows the change in travel frequency per non-grocery shopping destination as a result of gaining access to either an autonomous taxi or private AV. Again, for the majority of destinations, travel frequency would not be changed by the respondents (68%), although there are more frequency changes noticeable than for work/education destinations. This seems logical, as work/education travel is often mandatory and travel frequency is therefore less flexible than for shopping travel. 14% of the destinations is visited more often, which could be because the AV makes them more attractive to visit, or because the AV enables the respondent to visit a certain destination. 18% of the destinations is visited less often, which could be because the AV enables respondents to carry more products than their currently used transportation mode, reducing the need for additional trips. Otherwise, travel frequency to a destination could decline because respondents choose to visit other destinations instead with the AV.

Table 4.13: Change in travel frequency per destination due to owning an AV or being able to use an autonomous taxi, for non-grocery shopping travel

Change in travel frequency due to AV	
Lower frequency	18%
Same frequency	68%
Higher frequency	14%

Table 4.14 shows the change in average trip length for non-grocery shopping trips after the introduction of an AV. Trip length is measured as the 'estimated average door-to-door travel time per car' to a shopping destination. Similarly to travel frequency, the average trip length for non-grocery shopping trips will not change for most individuals (66%). However, a considerable percentage of the respondents (23%) would increase their average trip length by an average of 4.4 minutes. This indicates that the AVs cause people to favor other, farther away locations for their non-grocery shopping. 12% of the respondents would actually decrease their average trip length after gaining access to an AV, by 2.4 minutes on average. An explanation for this could be that they would have to travel to far locations comparatively less often because they can use the storage capacity of AVs to purchase more goods per visit.

Table 4.14: Change in average trip length per respondent due to owning an AV or being able to use an autonomous taxi, for non-grocery shopping travel

Change in average trip length due to AV		Avg. increase/decrease
Increase avg. trip length	23%	+4.4 minutes
Same avg. trip length	66%	0.0 minutes
Decreased avg. trip length	12%	-2.4 minutes

4.4 Factors influencing the impact of AVs on travel demand

This section discusses the results from 8 ordinal regression models, with the main goal of identifying relevant factors that influence the impact of automated driving on travel demand. These factors can be subdivided into three categories: Attribute levels of the AV, context characteristics and socio-demographic characteristics. The final models presented in this chapter include only the attribute levels and significant explanatory variables.

Each model is described by a table with model information such as model fit and significance, a table with parameters and their significance, and a figure illustrating the threshold parameters. The significance of each parameter is indicated by a number of asterisks: * = (p<0.1), ** = (p<0.05) and *** = (p<0.01). The explanatory variables, except for the attributes, have been ordered based on the value of their corresponding parameter, which indicates relative effect size. The full models, also including all insignificant parameters, can be seen in appendix 4 through 11.

Model 1: AV usage for work/education travel

Table 4.15+4.16 and figure 4.11 describe the results of model 1. Although the final model is a significant improvement over the restricted model, the predictive power of the final model is barely adequate (R^2=0.104). All attributes are relevant, although not each attribute level is significant. For example, there are no statistically proven differences between LVL 3/4 <> LVL 5 AVs, moderately safe <> 25% safer AVs and moderately fast <> 15% faster AVs. However, autonomous taxis (as opposed to private AVs), 15% more expensive AVs and 15% slower AVs are used less often while AVs that have a 75% reduced change of being involved in accidents and 15% cheaper AVs are used more often. The current usage percentage of all transportation modes are negatively correlated to AV usage compared to the current usage percentage of cars. This is logical, because of all transportation modes, private AVs and autonomous taxis are most similar to cars. However, current train and bus/subway/tram users are more likely to use the AV than cyclists and pedestrians. High education is negatively correlated to AV usage, possibly because these individuals are less likely to change their habits. Owning a large car is also negatively correlated to AV usage, which could be because high-cost vehicles indicate a passion for (manual) driving. The AV usage percentage increases with longer travel distances.

Table 4.15: AV usage for work/education travel model statistics

	LL	Chi^2	D.f.	Sign.
Restricted model	-3931.76			
Final model	-3523.83	815.85	18	0.000
McFadden Pseudo R^2	0.104			

Table 4.16: AV usage for work/education travel model parameters

Parameter	Coefficient	Significance
AV = private LVL 5	-0.00049	
AV = autonomous taxi	-0.25594	***
AV = 25% safer than regular car	-0.02575	
AV = 75% safer than regular car	0.15326	***
AV = 15% faster than regular car	0.01073	
AV = 15% slower than regular car	-0.13061	**
AV = 15% cheaper than regular car	0.09999	*
AV = 15% more expensive than regular car	-0.14142	***
Current usage percentage walking *0.01	-1.59984	***
Current usage percentage unknown *0.01	-1.54942	***
Current usage percentage bicycle *0.01	-1.32951	***
Current usage percentage train *0.01	-1.02711	***
Current usage percentage bus/subway/tram *0.01	-0.76027	***
Individual follows a part-time education	0.20773	***
Individual has a large-middle class or top class car	-0.18839	***
Individual is highly educated	-0.09949	**
Expected two-way travel duration increase with AV in minutes	-0.01065	***
Estimated average one-way door-to-door travel time per car in min.	0.00502	***
Threshold parameter 0 – 10-30% AV usage	-1.27833	***
Threshold parameter 1 – 40-60% AV usage	-0.87079	***
Threshold parameter 2 – 70-90% AV usage	-0.54033	***
Threshold parameter 3 – 100% AV usage	-0.12721	***

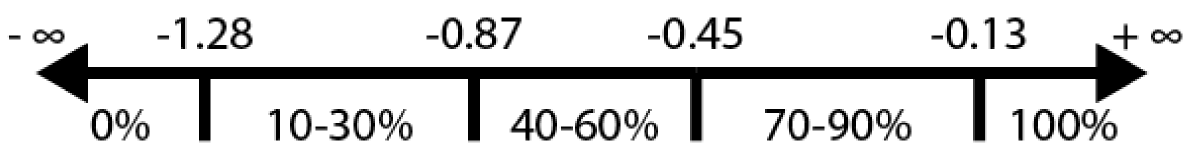


Figure 4.11: AV usage percentage for work/education travel threshold axis

Model 2: AV usage for non-grocery shopping travel

Table 4.17+4.18 and figure 4.12 describe the results of model 2. For non-grocery shopping travel, the AV attributes have similar effects on AV usage as for work/education travel. However, 15% cheaper AVs no longer have a positive effect on AV usage. Car owners, males and large household members are more likely to use the AV, while the highly educated, aged 50 plus and rural dwellers are negatively correlated with AV usage for non-grocery shopping travel. AVs are used more often for visits to local shopping centers than city centers, which could indicate that AVs are more likely to be used for utilitarian shopping than leisure shopping, or that individuals are still avoiding parking issues in the center with private AVs. Finally, AVs are used more often if considerable time can be saved by switching transportation modes.

Table 4.17: AV usage for non-grocery shopping travel model statistics

	LL	Chi^2	D.f.	Sign.
Restricted model	-7743.88			
Final model	-7004.88	1478.00	24	0.000
McFadden Pseudo R^2	0.095			

Table 4.18: AV usage for non-grocery shopping travel model parameters

Parameter	Coefficient	Significance
AV = private LVL 5	0.03275	
AV = autonomous taxi	-0.22656	***
AV = 25% safer than regular car	-0.00526	
AV = 75% safer than regular car	0.258	***
AV = 15% faster than regular car	-0.04005	
AV = 15% slower than regular car	-0.11407	***
AV = 15% cheaper than regular car	0.03326	
AV = 15% more expensive than regular car	-0.28597	***
Current usage percentage walking *0.01	-1.39751	***
Current usage percentage bicycle *0.01	-1.20525	***
Current usage percentage other transportation modes *0.01	-1.09718	***
Current usage percentage train *0.01	-0.94889	***
Current usage percentage bus/subway/tram *0.01	-0.66508	***
Current usage percentage unknown *0.01	-0.50096	***
Individual's household owns (or leases) a car	0.16129	**
Individual is aged 50 years or older	-0.13953	**
Individual lives in rural area	-0.13188	***
Individual is male	0.11839	***
Destination type is 'Local shopping center'	0.11175	***
Destination type is 'City center'	-0.09243	***
Individual's household size is 3 or more (no student housing included)	0.07529	**
Individual is highly educated	-0.06771	***
Expected two-way travel duration increase with AV in minutes	-0.01031	***
Estimated average one-way door-to-door travel time per car in min.	0.00653	***
Threshold parameter 0 – 10-30% AV usage	-1.1607	***
Threshold parameter 1 – 40-60% AVusage	-0.78348	***
Threshold parameter 2 – 70-90% AVusage	-0.38486	***
Threshold parameter 3 – 100% AV usage	0.11787	***

Figure 4.12: AV usage percentage for non-grocery shopping travel threshold axis

Model 3: Change in public transportation (PT) usage for work/education travel

Table 4.19+4.20 and figure 4.13 describe the results of model 3. This model only uses data from current PT users to see whether they would change their PT usage for certain destinations. The final model has a rather weak predictive power (R^2=0.045), meaning it cannot explain most of the variance between cases. The only highly significant AV attribute level in this model is ‘75% less chance on an accident than regular cars’. It is positively related to a decline in PT usage, implying that travel safety is an important aspect for regular PT commuters. Males and the highly educated are less likely to give up PT usage in favor of the AV. Individuals living in highly urbanized areas are also less likely to give up PT usage, possibly because are using these transportation modes to avoid road congestion. Fulltime students and aged 40-49 are more likely to give up PT usage in favor of an AV alternative.

Table 4.19: Change in public transportation usage for work/education travel model statistics

	LL	Chi^2	D.f.	Sign.
Restricted model	-618.84			
Final model	-590.92	55.83	13	0.000
McFadden Pseudo R^2	0.045			

Table 4.20: Change in public transportation usage for work/education travel model description

Parameter	Coefficient	Significance
AV = private LVL 5	-0.0477	
AV = autonomous taxi	0.01633	
AV = 25% safer than regular car	0.10265	
AV = 75% safer than regular car	0.32363	***
AV = 15% faster than regular car	0.05917	
AV = 15% slower than regular car	-0.0373	
AV = 15% cheaper than regular car	0.03302	
AV = 15% more expensive than regular car	-0.1991	*
Individual is male	-0.3702	***
Individual is highly educated	-0.2851	**
Individual follows a fulltime education	0.31836	***
Individual is aged 40 to 49 years	0.23897	**
Individual lives in highly urbanized area	-0.2502	**
Threshold parameter 0 – Reduced PT usage	-0.6102	***
Threshold parameter 1 – No more PT usage	0.58783	***

Figure 4.13: Change in public transportation usage for work/education travel threshold axis

Model 4: Change in bicycle usage for work/education travel

Table 4.21+4.22 and figure 4.14 describe the results of model 4. This model only uses data from current bicycle users to see whether they would change their bicycle usage for certain work/education destinations. Similarly to the previous model that analyzes the change PT usage, this model has a rather poor predictive power (R^2=0.042). The only significant attribute of AVs in this model is whether it's privately owned or an autonomous taxi. Taxis are positively correlated to a decline in bicycle usage. Car ownership is negatively correlated to a decline in bicycle usage, which implies that an important reason for individuals to commute per bicycle is that they do not have a car available. Living in highly urban- or sub-urban areas and being highly educated are negatively correlated with giving up cycling, while males, large household members and aged 50 plus are positively correlated with a decline in cycling. Cycling usage percentage declines more at longer trips.

Table 4.21: Change in bicycle usage for work/education travel model statistics

	LL	Chi^2	D.f.	Sign.
Restricted model	-821.70			
Final model	-787.04	69.31	18	0.000
McFadden Pseudo R^2	0.042			

Table 4.22: Change in bicycle usage for work/education travel model parameters

Parameter	Coefficient	Significance
AV = private LVL 5	0.06689	
AV = autonomous taxi	0.26786	***
AV = 25% safer than regular car	-0.0472	
AV = 75% safer than regular car	0.15838	
AV = 15% faster than regular car	0.09479	
AV = 15% slower than regular car	-0.0604	
AV = 15% cheaper than regular car	0.14202	
AV = 15% more expensive than regular car	-0.0958	
Individual lives in sub-urban area	-0.3663	***
Individual lives in highly urbanized area	-0.3474	***
Individual's household owns (or leases) a car	-0.2244	**
Individual is highly educated	-0.2123	**
Individual is male	0.20056	**
Individual's household size is 3 or more (no student housing included)	0.19485	**
Individual is aged 50 years or older	0.18595	**
Number of days per week working or studying from home	0.08183	**
Expected two-way travel duration increase with AV in minutes	-0.0083	***
Estimated average one-way door-to-door travel time per car in min.	0.00785	***
Threshold parameter 0 – Reduced bicycle usage	0.15778	
Threshold parameter 1 – No more bicycle usage	1.24591	***

Figure 4.14: Change in bicycle usage for work/education travel threshold axis

MODEL 5: CHANGE IN BICYCLE USAGE FOR NON-GROCERY SHOPPING TRAVEL

Table 4.23+4.24 and figure 4.15 describe the results of model 5. This model has a poor predictive power (R^2=0.031). Therefore, the following parameters, although significant, cannot explain the change in bicycle usage to a large extent. This expresses itself in some peculiar correlations, such as the negative effect of 25% safer AVs on the willingness to give up bicycle usage. Other, more logical correlations are the positive relationship between autonomous taxis and a decline in bicycle usage, and a negative relationship between 15% more expensive AVs (compared to regular cars) and a decline in bicycle usage. Respondents are more likely to give up cycling for visits to themed shopping centers, probably because bicycles are less suitable to travel to peripheral locations and to transport large products typically sold at these centers. Owning a driver's license, being 40 years or older and high education are negatively correlated with a decline in bicycle usage for non-grocery shopping travel. Males, large household members and part-time students are more likely to give up cycling. Long travel distance is again positively correlated with declining bicycle usage.

Table 4.23: Change in bicycle usage for non-grocery shopping travel model statistics

	LL	Chi^2	D.f.	Sign.
Restricted model	-1700.54			
Final model	-1647.90	105.29	19	0.000
McFadden Pseudo R^2	0.031			

Table 4.24: Change in bicycle usage for non-grocery shopping travel model parameters

Parameter	Coefficient	Significance
AV = private LVL 5	0.09743	
AV = autonomous taxi	0.24225	***
AV = 25% safer than regular car	-0.1401	**
AV = 75% safer than regular car	0.10219	
AV = 15% faster than regular car	0.10339	
AV = 15% slower than regular car	-0.0588	
AV = 15% cheaper than regular car	0.01793	
AV = 15% more expensive than regular car	-0.1797	***
Destination type is 'Themed shopping center'	0.31162	***
Individual has a valid driver's license	-0.2345	**
Individual is aged 50 years or older	-0.1908	***
Individual is aged 40 to 49 years	-0.1771	**
Destination type is 'Local shopping center'	0.1767	***
Individual's household size is 3 or more (no student housing included)	0.17318	***
Individual follows a part-time education	0.17027	**
Individual is male	0.16539	***
Individual is highly educated	-0.1633	***
Expected two-way travel duration increase with AV in minutes	-0.0127	***
Estimated average one-way door-to-door travel time per car in min.	0.00716	***
Threshold parameter 0 – Reduced bicycle usage	-0.0719	
Threshold parameter 1 – No more bicycle usage	1.14147	***

Figure 4.15: Change in bicycle usage for non-grocery shopping travel threshold axis

MODEL 6: CHANGE TRAVEL FREQUENCY TO WORK/EDUCATION DESTINATIONS

Table 4.25+4.26 and figure 4.16 describe the results of model 6. The following two models investigate the tendency to increase weekly travel frequency towards certain destinations. This model, concerned with work/education destinations, has a rather poor predictive power (R^2=0.054). Of all the attributes, only 15% faster AVs are related significantly to an increased frequency. Strangely, very safe AVs are negatively related to travel frequency, although the significance level of this attribute level is questionable. Fulltime education destinations are more positively related to increased travel frequency than fulltime/part-time work destinations and part-time education destinations. Even though being highly educated proved to be consistently negatively correlated with changing transportation mode, it is positively correlated with increasing overall travel frequency towards work/education locations, indicating they would use the improved mobility of AVs to go to work/study more often. Current bus/subway/tram users, fulltime workers and driver's license owners are also more likely to increase travel frequency with the AV.

Table 4.25: Change travel frequency to work/education destinations model statistics

	LL	Chi^2	D.f.	Sign.
Restricted model	-1555.40			
Final model	-1471.62	167.55	17	0.000
McFadden Pseudo R^2	0.054			

Table 4.26: Change travel frequency to work/education destinations model parameters

Parameter	Coefficient	Significance
AV = private LVL 5	0.04064	
AV = autonomous taxi	-0.0914	
AV = 25% safer than regular car	-0.0761	
AV = 75% safer than regular car	-0.1161	*
AV = 15% faster than regular car	0.16142	**
AV = 15% slower than regular car	0.08889	
AV = 15% cheaper than regular car	0.00467	
AV = 15% more expensive than regular car	-0.0057	
Destination is fulltime education facility	1.16279	***
Destination is part-time job location	0.97226	***
Individual has a fulltime job	0.84667	***
Trip motive is part-time education facility	0.82332	***
Individual has a valid driver's license	0.44428	***
Current usage percentage of bus/subway/tram*0.01	0.32375	**
Individual is highly educated	0.12934	**
Expected two-way travel duration increase with AV in minutes	-0.0164	***
Expected trip cost increase with AV in euros	0.00501	***
Threshold parameter 0 – No difference in weekly travel frequency	-0.2841	
Threshold parameter 1 – Increased weekly travel frequency	2.67321	***

Figure 4.16: Change travel frequency to work/education destinations threshold axis

MODEL 7: CHANGE TRAVEL FREQUENCY TO NON-GROCERY SHOPPING DESTINATIONS

Table 4.27+4.28 and figure 4.17 describe the results of model 7. In spite of the numerous significant parameters, this model has poor predictive power (R^2=0.030). For non-grocery shopping, autonomous taxis induce a lower trip frequency (as compared to privately owned AVs). Short distance destinations such as local shopping centers, cycling trips and walking trips are negatively correlated with increasing travel frequency. Non-car ownership is related to an increasing travel frequency, indicating that AVs are being used to satisfy latent travel demand of non-drivers. Amongst other characteristics, females, highly urban and sub-urban dwellers, driver's license owners, aged 29 or younger and the highly educated are positively correlated to increasing travel frequency.

Table 4.27: Change travel frequency to non-grocery shopping destinations model statistics

	LL	Chi^2	D.f.	Sign.
Restricted model	-4576.22			
Final model	-4438.31	275.82	24	0.000
McFadden Pseudo R^2	0.030			

Table 4.28: Change travel frequency to non-grocery shopping destinations model parameters

Parameter	Coefficient	Significance
AV = private LVL 5	0.00794	
AV = autonomous taxi	-0.1224	***
AV = 25% safer than regular car	-0.0327	
AV = 75% safer than regular car	0.04518	
AV = 15% faster than regular car	0.08171	**
AV = 15% slower than regular car	0.04672	
AV = 15% cheaper than regular car	0.09119	**
AV = 15% more expensive than regular car	-0.0668	*
Current usage percentage unknown *0.01	0.37155	***
Current usage percentage bicycle *0.01	-0.2546	***
Destination type is 'Local shopping center'	-0.2327	***
Current usage percentage walking *0.01	-0.224	***
Individual's household owns (or leases) a car	-0.2085	***
Individual lives in highly urbanized area	0.17459	***
Individual is male	-0.1627	***
Individual has a valid driver's license	0.16027	**
Individual is aged 29 years or younger	0.15417	***
Individual lives in sub-urban area	0.14733	***
Individual is highly educated	0.09584	***
Trip motive is part-time education	0.09113	**
Individual drives a mini class or compact class car	0.07813	**
Individual is aged 40 to 49 years	0.07361	**
Expected two-way travel duration increase with AV in minutes	-0.0041	**
Estimated average one-way door-to-door travel time per car in min.	0.00364	***
Threshold parameter 0 – No difference in weekly travel frequency	-0.84637	***
Threshold parameter 1 – Increased weekly travel frequency	1.21575	***

Figure 4.17: Change travel frequency to non-grocery shopping destinations threshold axis

Model 8: Change in average trip length of non-grocery shopping trips

Table 4.29+4.30 and figure 4.18 describe the results of model 8. This model has negligible predictive strength (R^2=0.008), although it is still significant. The most notable outcome is that car ownership is again negatively related to increased travel with the AV, strengthening the hypothesis that AVs will be used by non-drivers to satisfy their latent travel demand.

Table 4.29: Change in average trip length of non-grocery shopping trip model statistics

	LL	Chi^2	D.f.	Sign.
Restricted model	-2096.85			
Final model	-2079.92	33.87	12	0.001
McFadden Pseudo R^2	0.008			

Table 4.30: Change in average trip length of non-grocery shopping trip model parameters

Parameter	Coefficient	Significance
AV = private LVL 5	-0.0333	
AV = autonomous taxi	-0.1022	*
AV = 25% safer than regular car	0.03138	
AV = 75% safer than regular car	0.10573	*
AV = 15% faster than regular car	0.09983	*
AV = 15% slower than regular car	0.10229	*
AV = 15% cheaper than regular car	0.12273	**
AV = 15% more expensive than regular car	-0.0218	
Individual's household owns (or leases) a car	-0.1877	***
Individual has a mini class or compact class car	0.15344	***
Individual is aged 40 to 49 years	0.10655	*
Individual lives in sub-urban area	0.08871	*
Threshold parameter 0 – No difference in average trip length	-0.854	***
Threshold parameter 1 – Increased average trip length	0.86402	***

Figure 4.18: Change in average trip length of non-grocery shopping trip threshold axis

4.5 Summary of results

If everybody in the Netherlands would have access to an AV, automated driving could lead to a 20-25% increase in vehicle-hours travelled (VHT) by car for work/education and non-grocery shopping travel. Of all transportation modes, the modal shares of public transportation modes are expected to decline the most, by approximately 40-55% for all scenarios. Active transportation modes are also expected to decline considerably by approximately 20-30% for each scenario. Most individuals would not change their travel frequency after gaining access to an AV (70-80%). Most repondents don't change their average trip length either, although the respondents that do tend to go to farther away destinations: 23% of the respondents indicated a higher average non-grocery shopping trip length if they could use an AV.

All of the attributes: AV type, safety, travel time and travel cost, have a significant influence on changes in travel demand. Autonomous taxis are used significantly less than private AVs, except for trips that are currently made per bicycle. However, there is no significant difference between the usage of AVs that can drive autonomously anywhere, or just on the highways (resp. LVL 5 and LVL 3/4). A 75% safety improvement of AVs over regular cars is correlated to higher AV usage, increased travel frequency and a decline of public transportation usage, but a small improvement of 25% decreased chance on an accident does not significantly influence travel demand. Travel time improvements are correlated to a higher AV usage percentage, increased travel frequency and a decline in bicycle usage. Trip cost improvements are mainly related to a higher AV usage percentage and travel frequency for non-grocery shopping travel, but less so for work/education purposes.

Many socio-demographic characteristics are statistically related to changes in travel demand in this study. Non-car owners are more likely to switch from PT to the AV and to increase work/education travel frequency and average shopping trip length with the AV. Highly education individuals are less likely to make changes their transportation mode choice due to AV availability, but more likely to use AVs to increase travel frequency for both work/education and shopping. Females are more likely to increase their travel frequency to shopping destinations with the AV and also more likely to switch from PT to an AV, but less likely to decline or give up bicycle usage in favor of an AV than males. Individuals aged 50 plus are less likely to change their transportation mode choice due to AV availability for non-grocery shopping trips, but more likely to switch from PT to an AV for work/education trips. Members of large households, not including student residences, are more willing to use AVs for work/education purposes, and more willing to give up bicycling for shopping trips in favor of an AV.

Finally, there are a number of relevant contextual factors. In highly urbanized areas, individuals are less likely to switch from PT or bicycle to AV usage, although they are more inclined to use the AV to increase their travel frequency to work/education locations. Residents of rural areas are less likely to use AVs for non-grocery shopping purposes. When making non-grocery shopping trips, individuals tend to switch from their current transportation mode to an AV more often for visits to local shopping centers than city centers. However, they are the least inclined to increase travel frequency to local shopping centers, in comparison with other shopping center types. Individuals are most likely to change from bicycle to AV for shopping trips to themed shopping centers. A higher trip length is positively correlated to both changes in transportation mode (towards AV usage) and increased travel frequency for both work/education and non-grocery shopping travel.

5 Conclusion

The purpose of this study has been to find evidence for the influence of automated driving on travel demand and to investigate which factors are related to this impact. Given the complexity of this question, several sub-questions were formulated to approach the problem stepwise. This chapter will discuss the findings of the research questions and their implications. Furthermore, several policy recommendations will be made. The chapter concludes with a discussion of the research method and recommendation for further research.

5.1 Results and implications

Automated driving has many benefits over regular driving, due to their technical capabilities. Level 5 automated vehicles (AVs) can drive completely autonomously and can therefore travel unmanned. This enables automated parking and driverless taxis. Even though the technology behind automated driving still needs to be perfected, it is expected that automated driving will take over manual driving in the future. Therefore, it is important to assess the potential impacts of automated driving on society so stakeholders can anticipate to the opportunities and threats, and make automated driving a success. There are still many uncertainties regarding the impacts of automated driving. One of the largest uncertainties is the impact on the transportation system. One the one hand, AVs could improve road capacity and reduce traffic accidents, leading to better traffic flow. On the other hand, AVs could lead to a higher travel demand due to unmanned travel and high travel utility. The 'behavioral' impacts of automated driving on travel demand are very underexposed in the literature.

The results of this study indicate that if every person in the Netherlands would own a level 3/4 or level 5 AV, the usage of cars for work/education trips could increase by approximately 20% and usage of cars for non-grocery shopping trips could increase by 35%. If instead of owning an AV, every person in the Netherlands could use an autonomous taxi service with similar travel time and costs compared to private car travel, the modal share of these taxis would be approximately 50% for both work/education and non-grocery trips.

Public transportation (PT) usage in all scenarios with AVs would decline by 40-55%. Females, the lower educated, students, people aged 40-49 years and people *not* living in highly urban areas are more likely to reduce or give up their usage of PT for work/education trips. Bicycle usage would decline by 20-30% in all scenarios with AVs. Males, the lower educated, people living in large households (3+) and non-drivers are more likely to reduce or give up their use of bicycles. People aged over 50 years old are more likely to give up cycling for work/education trips, but less likely to give up cycling for non-grocery shopping. These results show similarities with the outcome of the questionnaire by the Boston Consulting Group (2016), which indicated a decline in PT and bicycle usage of respectively 50-70% and 30%.

Furthermore, little evidence was found that automated driving will lead to a higher trip frequency for work/education or non-grocery shopping travel. Between 70-80% of the destinations are not visited more or less often, while there are equally many destinations visited more often, as there are destinations visited less often, for both work/education and non-grocery shopping. A reason for individuals to visit their work/education less often is that they use their time traveling with the AV to work, enabling to take a day off later. Individuals might visit non-grocery destinations less often because they intend to use the AV to shop at other, more preferred locations instead. High education, having a driver's license, current usage of PT and significant travel time and cost improvements of traveling with the AV are related to an increase travel frequency for work/education destinations. Among other factors, long distance trips, females, living in a highly urbanized area and being aged 29 years or younger are related to higher travel frequency for non-grocery shopping destinations. Furthermore, it is concluded that approximately one of every five persons would increase their average trip length for non-grocery shopping. This reinforces the hypotheses made by Gruel & Stanford (2016), Gucwa (2014) and Pendyala & Bhat (2014)that automated driving could increase average trip length.

In general, the attributes of AVs that seem related to a higher impacts on travel demand are private AV ownership, 75% less chance on accidents and travel time and –cost benefits of the AV. Unfortunately, due to the choice to use a low number of unique profiles in the experiment, no interaction effects can be estimated between attributes.

The results show that automated driving could significantly increase car usage, but will only have a moderate effect on travel frequency and trip length, for work/education and non-grocery shopping trips. These impacts could have implications for the demand for infrastructure, because working trips are often made during peak times. Another implication of the results is that automated driving will not easily change individuals' habits regarding the non-grocery shopping locations they visit and how often they visit them. Only 13% of the respondents indicated that they would visit currently not visited non-grocery shopping locations if they could use an AV.

5.2 Policy recommendations

AVs could have a dramatic effect on the amount of car traffic. The effect could already be present in the 'early' stages of automation (level 3/4 AVs, only automated driving on highways), a scenario which could occur within the next 10-30 years in the Netherlands (Netherlands Institute for Transport Policy Analysis, 2017). To find the demand for infrastructure due to automated driving, a holistic model is needed to determine the combined operational and behavioral impacts of automated driving on travel demand (Gruel & Stanford, 2016).

Governments are advised to take the effects of automated driving on travel demand into account when making spatial plans, in order to deal with the additional traffic this causes. An option could be to creating dedicated AV lanes in which vehicles are allowed to drive with a very short headway, increasing road capacity. This solution would however disadvantage other road traffic. Another solution to reduce car traffic is to stimulate the usage of autonomous taxis for transfers to and from mass transit hubs (Alessandrini et al., 2015). This could be achieved by building high-capacity autonomous taxi-depots at these locations. Finally, regulations could be made regarding the share of unmanned kilometers that autonomous taxis and AVs are allowed to make, for instance to prevent them from driving around to avoid parking fees.

For businesses involved in the sales, usage or development of AVs, it is advisory to pay attention in advertising campaigns on the safety improvement aspects of automated driving. Based on this study, the most attractive target group for an affordable autonomous taxi service could be working class, young parents, living in rural areas.

5.3 Discussion

This research used a stated choice experiment to collect data regarding the impact of automated driving on travel demand, because revealed data is unobtainable. However, there are several issues with the research approach.

Firstly, it is questionable how vividly respondents can image themselves in the proposed situation. For those who are not familiar with automated driving, the short introduction of AVs in the questionnaire may not have been enough information to give them a good image of their technical capabilities. And even if it did, it is questionable whether the respondents have taken their time to consider all the possibilities and drawbacks of automated driving before making their decisions.

Secondly, it might be impossible for respondents to predict certain behavioral changes such as their travel frequency to a certain location, because this change is a process that develops gradually after getting more experience with automated driving. It could take several months or years for an individual to change their activity-travel patterns, so predicting this change in advance can be very hard.

Thirdly, length of the questionnaire was kept to a minimum to decrease the burden on respondents. This resulted in the consideration of several trips by motive, rather than a complete activity-travel pattern. However, this means some important constraints, such as car availability for certain trips and restricted transportation mode choice due to trip chaining, cannot be accounted for in the results. Even though there were no comments from the respondents regarding these issues, it is possible that these constraints could have had a latent effect.

Fourth, a few respondents indicated that they found the choice experiment rather complicated because of an overload of information regarding the specifications of the AV. Other respondents indicated that the questionnaire was too long. It is therefore questionable whether the respondents were able to consider all of the AV attributes carefully in each choice task. Furthermore, it is believed that respondents need a few trials before they are acquainted enough with the questioning of stated choice experiments (Hensher et al., 2005). Since there were only three choice tasks and one trial, this may have affected the results.

Fifth, there are some concerns regarding the complexity of questions and whether they were fully understood by the respondents. It is suspected that a small portion of the individuals have misinterpreted the question regarding trip frequency in the experiment. A share of the respondents (approximately 10%) has indicated that they would travel *much* less to a work / education destination after gaining access to an AV, for which there is no explanation. These respondents may have misinterpreted the question as 'What will be your trip with the AV' instead of 'What will be your total trip frequency, if you could use the AV'.

Sixth, the high usage percentage of autonomous taxis indicated by the respondents may have been caused by the fact that they were presented very favorably in the experiment. For example, the travel costs involved in autonomous taxi travel was very low and would probably be higher in reality. Also, it is questionable whether the respondents considered all required actions that are conditional for traveling per autonomous taxi, such as ordering the taxi and waiting for the taxi to arrive. In the description of the taxi in the experiment, it was briefly mentioned that this was necessary and that the taxi would always arrive soon after placing the order.

Seventh, unlike travel demand models, this experiment does not consider road capacity restraints. The car usage increase due to automated driving indicated by the respondents would in reality be tempered by the fact that all the extra car traffic would cause congestion and therefore longer travel times with the AV.

For further researches similar to this study, it is recommended to focus questionnaires specifically on autonomous taxis or private AVs, or to dedicate separate sections to them, so their specific attributes can be described in more detail to the respondents. Also, the impact of private car sharing on travel demand and the impact of additional attributes and contextual factors could be investigated.

Future research should also focus on other behavioral impacts of automated driving, such as long term decisions like car ownership and home- /work location choice, or the impact on departure time. Furthermore, advanced land use-transportation interaction (LUTI) models could be used to translate the behavioral impact of automated driving to changes in land value and/or urban structures. This kind of research could be used to investigate the hypothesis that automated driving will lead to urban sprawl, for instance.

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Appendix 1: Summary of AV models and their implications for travel demand

Source	Network description	Fleet characteristics	Scenario description	Impact on VKT	Other results compared to base-case scenario (non-automated)
(Boston Consulting Group, 2016)	Amterdam region (2050)	Most vehicles automated, level 5 private only	Automated driving only allowed on highways	**+20%**	Public transport use down 14%
		Most vehicles automated, level 5 private and (publicly) shared	Automated driving only allowed on highways and main roads	**+100%**	Cycling down 27%, Public transport use down 48%
		All vehicles automated, level 5 private and (publicly) shared	Automated driving allowed anywhere	**+80%**	Cycling down 30%, Public transport use down 68%
		All vehicles automated, most are publicly shared	Automated driving allowed anywhere	**+30%**	Cycling down 30%, Public transport use down 68%
(Nordhoff, Van Arem, & Happee, 2016)	Delft, the Netherlands (abstract)	All vehicles automated, level 5 private only	Regular parking fees	**+17%**	
		All vehicles automated, level 5 private only	Regular parking fees,VTT halved	**+49%**	
		All vehicles automated, level 5 private only	No free parking at home, only free parking at 2 peripheral nodes	**+140%**	
		All vehicles automated, level 5 private only	No free parking at home, only free parking at 2 peripheral nodes, VTT halved	**+190%**	
(Kröger et al., 2016)	Germany (2035)	7.3% of vehicles level 3/4; 10.1% of vehicles level 5; all vehicles private	Minors from 14 y.o. can drive LVL5 AV, VOTT reduced 25% for Avs from the 11th minute travelling	**+2.4%**	Public transport use down 2.8%
		4.8% of vehicles level 3/4; 37.6% of vehicles level 5; all vehicles private	Minors from 14 y.o. can drive LVL5 AV, VTT reduced 25% for Avs from the 11th minute travelling	**+8.6%**	Public transport use down 10.6%

(Childress et al., 2014)	Puget Sound Region, Washington, US	All vehicles automated, level 3/4 private only	Capacity of highways and main roads increased 30%	**+3.6%**	VHT decreased by 3.9%, public transport use up 4%
		All vehicles automated, level 3/4 private only	Capacity of highways and main roads increased 30%, VTT reduced 65%	**+5%**	VHT decreased by 2.1%, public transport use up 4%
		All vehicles automated, level 3/4 private only	Capacity of highways and main roads increased 30%, VTT reduced 65% for, parking fees reduced 50%	**+19.6%**	VHT increased by 17.3%, public transport use down 8%
(Gucwa, 2014)	San Fransisco Bay Area	All vehicles automated, level 3/4 private only	Capacity of highways and main roads increased 100%	**+2%**	
		All vehicles automated, level 3/4 private only	Capacity of highways and main roads increased 10%, VTT halved	**+6.7%**	
		All vehicles automated, level 3/4 private only	Capacity of highways and main roads increased 100%, VTT halved	**+7.9%**	

Appendix 2: Respondents' remarks about the questionnaire

Abonnement wordt met 1 b geschreven ;-)

Boeiend concept

De auto's in de voorbeelden nemen het gebruik van mijn huidige auto over, omdat het qua kosten nooit duurder werd dan nu, en soms veiliger en ontspannender, soms enkel een fractie langzamer, hetgeen geen bezwaren voor me zijn. Dank u, en succes!

De zelfrijdende auto is wel aantrekkelijk, maar niet voor mij aangezien ik in de stad woon, werk, studeer etc en het met de fiets maximaal 15 minuten kost om ergens te komen. Dan is het de moeite en het geld niet waard

Een interessante propositie! Alleen bij de zelfrijdende auto's mis ik het gegeven of ik kan kiezen uit mijn huidige auto en de zelfrijdende auto of dat ik verondersteld word te beslissen of ik de zelfrijdende auto op de aangegeven manier wil gebruiken. Hopelijk beinvloedt het uw resultaten niet in ongunstige zin!?

erg leuk

erg leuk

Fijne enquete onderwerp

geen was wel leuk om in te vullen

goed

Goed onderwerp, vragen om echt over na te denken

goede enquete

Graag meer van deze vragenlijsten. Succes verder.

Graag wil ik u vertellen fat ik deze enquete erg update vond met betrekking tot de keuzes van auto's.

Heel leuk onderwerp.

Het gaat alleen maar om hele korte ritten. Fietsen is ook gezond. Het enige wat veranderd bij B is dat je niet zelf een parkeerplaats hoeft te zoeken. Dan gaan weeromstandigheden meespelen. Ik mis de mogelijkheid om zelf opmerkingen toe te voegen.

Het is abonnement i.p.v. abbonnement!

Het is goed maar ik ben niet goed genoege voor tijd .

Het verschil in auto maakt nog niet waarom ik hem vaker zou gebruiken. De frequentie voor werk of winkelen blijft namelijk hetzelfde.

Het was een leuk om in te vullen, overzichtelijk!

iets te lang

Ik ga niet meer reizen als ik over een zelfstandig rijdende auto zou beschikken. Het biedt wel mogelijkheden om al vast te werken vanuit je auto. Nu nog onvoorstelbaar allemaal maar mss over 10-12 jaar al net zo gewoon als de smartphone nu.

Ik kan niet wachten tot dat er echte zelfrijdende auto's zijn!

Ik miste de optie volledig autonome auto die niet mijn eigendom is en goedkoper dan het zelf hebben van een auto bij weinig gebruik. Omdat een auto dan veel efficienter gerbuikt kan worden kunnen de afschrijving en onderhoud over meer mensen verdeeld worden waardoor de totale kosten per kilometer goedkoper moeten kunnen dan nu het geval is. Ook zou het openbaar vervoer veel goedkoper moeten kunnen doordat er geen chaufeur meer nodig zal zijn!

Ik vind de toelichting nog niet helemaal duidelijk.

Ik werk in de wijk waar ik woon en heb geen tot bijna geen reistijd

Ik zou niks veranderen aan mijn autogebruik. Ik rijd auto wanneer het nodig is en fiets wanneer het kan.

In het algemeen hoop ik niet dat deze auto's er gaan komen. Ik hoop dat de mensen zelf auto kunnen blijven rijden.

interessant

Interessante enquete.....

interessante vragenlijst

irritante enquete . de antwoorden kan je negeren

is leuk

Is vrij moeilijk in te vullen. Je moet goed kijken en nadenken voor dat je iets invult.

Kom maar op met die zelfrijdende auto's

leuk om in te vullen

Leuk on mee te doyen

Leuk onderzoek om aan deel te nemen.

Leuk onderzoek, goed opgezet en succes met het onderzoek!

leuk!

Leuke enquete

Leuke enquete!!

Leuke enquete!!

leuke enquette

leuke vrageblijst

Leuke vragen

leuke vragenlijst

leuke vragenlijst

LEUKE VRAGENLIJST OM IN TE VULLEN

Mooi gedaan!

Omslachtige vragen en niet duidelijk

Onduidelijk of aangegeven reiskosten als goedkoper dan wel duurder vermeld staan

qua overzichtelijkheid wat betreft de onderscheidende eigenschappen van auto's A, B en C is het wellicht een beter idee om deze in 1 grote tabel dan de manier waarop het nu is gedaan: per soort dezelfde vragen.

Succes er mee!

Toelichting: ik heb wel een rijbewijs en gebruik ook wel eens een (huur-) auto, maar eigenlijk alleen voor bestemmingen die niet gemakkelijk per OV of fiets te bereiken zijn. Ik geef de voorkeur aan fietsen omdat dit beter voor mij is. Dan beweeg ik nog eens wat; ik heb een zittend beroep en houd niet van sport. Dus ook al wordt zo'n zelfrijdende auto nog zo goedkoop en milieuvriendelijk: ik zal er toch niet voor kiezen, om gezondheidsredenen voornamelijk. Succes gewenst met uw onderzoek!

vreemde vraagstelling

Zeer interessant onderwerp om mijn mening over te gevenn

Zeer leuk en zeer interessant onderwerp

Appendix 3 – Legend for NLOGIT output parameters

AV attributes	
X11_LVL5	AV = private LVL 5
X12_TAXI	AV = autonomous taxi
X21_SF25	AV = 25% safer than regular car
X22_SF75	AV = 75% safer than regular car
X31_FAST	AV = 15% faster than regular car
X32_SLOW	AV = 15% slower than regular car
X41_CHP	AV = 15% cheaper than regular car
X42_EXP	AV = 15% more expensive than regular car
Context characteristics	
C_TRAIN	Current usage percentage train *0.01
C_BUS	Current usage percentage bus/subway/tram *0.01
C_BIKE	Current usage percentage bicycle *0.01
C_WALK	Current usage percentage walking *0.01
C_OTHER:	Current usage percentage other transportation modes *0.01
C_UNKN	Current usage percentage unknown *0.01
ACT_FTS	Trip motive = fulltime education
ACT_PTB	Trip motive = part-time job
ACT_PTS	Trip motive = part-time education
C_TTCAR	Estimated average one-way door-to-door travel time per car in min.
C_TTDIFF	Expected two-way travel duration increase with AV in minutes
C_TCDIFF	Expected trip cost increase with AV in euros
C_HOMEFQ	Number of days per week working or studying from home
C_FREQ	Weekly travel frequency to a location
Socio-demographic characteristics	
HAS_CAR	Individual's household owns (or leases) a car
MALE	Individual is male
DR_LCNSE	Individual has a valid driver's license
EDUC_HIG	Individual is highly educated
OCC_FTJ	Individual follows a fulltime education
OCC_PTJ	Individual has a part-time job
OCC_PTS	Individual follows a part-time education
STUDHOUS	Individual lives in student residence
SIZE_3MR	Individual's household size is 3 or more (no student housing included)
CAR_TINY	Individual drives a mini class or compact class car
CAR_SMAL	Individual drives a small middle class car
CAR_LARG	Individual drives a large middle or top class car
AGE_U30	Individual is aged 29 years or younger
AGE_4049	Individual is aged 40 to 49 years
AGE_50PL	Individual is aged 50 years or older
HIGH_URB	Individual lives in highly urbanized area
SUBURBAN	Individual lives in sub-urban area
RURAL	Individual lives in rural area
T_THEMED	Destination type is 'Themed shopping center'
T_CENTER	Destination type is 'City center'
T_LOCAL	Destination type is 'Local shopping center'

Appendix 4 – Full model 1: AV usage for work/education travel

This appendix is an unaltered Nlogit output file. For the meaning of the coded parameters, please refer to the parameter legend of appendix 3 on page 90.

```
|-> SETPANEL ; Group = PAR_ID ; Pds = GR_COUNT $
|-> SKIP $
|-> ORDERED ;
    Lhs=SDV_U_5 ;
    Rhs=one,
    X11_LVL5,X12_TAXI,X21_SF25,X22_SF75,X31_FAST,X32_SLOW,X41_CHP,X42_EXP,
    C_TRAIN,C_BUS,C_BIKE,C_WALK,C_OTHER,C_UNKN,
    ACT_FTS,ACT_PTB,ACT_PTS,
    C_TTCAR,C_TTDIFF,C_TCDIFF,C_HOMEFQ,
    HAS_CAR,MALE,DR_LCNSE,EDUC_HIG,
    OCC_FTJ,OCC_PTJ,OCC_PTS,
    SIZE_3MR,
    CAR_TINY,CAR_SMAL,CAR_LARG,
    AGE_U30,AGE_4049,AGE_50PL,
    HIGH_URB,SUBURBAN,RURAL,
    ;panel $

----------------------------------------------------------------
Deleted     54 observations with missing data. N is now   2644
----------------------------------------------------------------
+--------------------------------------------------------------------+
| Variable = ____________ Variable Groups    Max    Min    Average |
| GR_COUNT   Group sizes  PAR_ID      724      6      1        3.7 |
+--------------------------------------------------------------------+
+------------------------------------------------------+
| Frequency count for group sizes of GR_COUNT          |
| Group size =   1   Pct =   1.24%   CumPct =   1.24%  |
| Group size =   2   Pct =   1.66%   CumPct =   2.90%  |
| Group size =   3   Pct =  73.62%   CumPct =  76.52%  |
| Group size =   4   Pct =    .55%   CumPct =  77.07%  |
| Group size =   5   Pct =    .00%   CumPct =  77.07%  |
| Group size =   6   Pct =  22.93%   CumPct = 100.00%  |
+------------------------------------------------------+
Normal exit:  48 iterations. Status=0, F=    3486.465

----------------------------------------------------------------------------
--
Ordered Probability Model
Dependent variable                SDV_U_5
Log likelihood function       -3486.46536
Restricted log likelihood     -3904.12356
Chi squared [  38 d.f.]         835.31640
Significance level                 .00000
McFadden Pseudo R-squared        .1069787
Estimation based on N =    2644, K =   42
Inf.Cr.AIC  =   7056.9 AIC/N =      2.669
Model estimated: Aug 14, 2017, 22:37:14
Underlying probabilities based on Normal
--------+-------------------------------------------------------------------
--
        |                  Standard            Prob.       95% Confidence
 SDV_U_5|  Coefficient       Error       z     |z|>Z*         Interval
--------+-------------------------------------------------------------------
--
        |Index function for probability
Constant|     1.21903***      .22409     5.44  .0000      .77982    1.65823
X11_LVL5|      .00242         .05480      .04  .9648    -.10498     .10982
X12_TAXI|    -.25889***       .05434    -4.76  .0000    -.36540    -.15238
X21_SF25|    -.03088          .05453     -.57  .5712    -.13777     .07600
X22_SF75|      .13959**       .05490     2.54  .0110     .03199     .24719
```

```
X31_FAST|      .03199          .05582       .57  .5666      -.07742     .14140
X32_SLOW|     -.11930**        .05542     -2.15  .0313      -.22792    -.01068
 X41_CHP|      .11494**        .05521      2.08  .0374       .00673     .22315
 X42_EXP|     -.12155**        .05499     -2.21  .0271      -.22933    -.01377
 C_TRAIN|    -1.04231***       .09763    -10.68  .0000     -1.23367    -.85095
   C_BUS|     -.85914***       .13873     -6.19  .0000     -1.13105    -.58722
  C_BIKE|    -1.33284***       .07860    -16.96  .0000     -1.48689   -1.17879
  C_WALK|    -1.54609***       .25029     -6.18  .0000     -2.03665   -1.05553
 C_OTHER|      .71630          .47056      1.52  .1279      -.20597    1.63858
  C_UNKN|    -1.56428***       .11145    -14.04  .0000     -1.78272   -1.34583
 ACT_FTS|      .19644          .18715      1.05  .2939      -.17036     .56324
 ACT_PTB|      .12613          .19767       .64  .5234      -.26130     .51357
 ACT_PTS|      .18440**        .08514      2.17  .0303       .01754     .35127
 C_TTCAR|      .00573***       .00116      4.93  .0000       .00345     .00800
C_TTDIFF|     -.01001***       .00219     -4.58  .0000      -.01430    -.00573
C_TCDIFF|     -.00355          .00315     -1.13  .2600      -.00972     .00262
C_HOMEFQ|      .00194          .01794       .11  .9138      -.03322     .03710
 HAS_CAR|      .04318          .08506       .51  .6117      -.12355     .20990
    MALE|      .04035          .04991       .81  .4188      -.05747     .13817
DR_LCNSE|     -.24941**        .11054     -2.26  .0241      -.46607    -.03276
EDUC_HIG|     -.10365**        .04939     -2.10  .0359      -.20046    -.00685
 OCC_FTJ|      .21974          .15796      1.39  .1642      -.08984     .52933
 OCC_PTJ|     -.01110          .14443      -.08  .9387      -.29418     .27198
 OCC_PTS|      .13058*         .06722      1.94  .0520      -.00116     .26232
SIZE_3MR|      .03486          .04896       .71  .4765      -.06111     .13082
CAR_TINY|     -.01831          .06572      -.28  .7806      -.14711     .11050
CAR_SMAL|     -.03629          .06737      -.54  .5901      -.16833     .09575
CAR_LARG|     -.22128***       .07632     -2.90  .0037      -.37087    -.07169
 AGE_U30|      .11229          .08927      1.26  .2085      -.06268     .28726
AGE_4049|      .03175          .06251       .51  .6116      -.09077     .15427
AGE_50PL|      .11619*         .06080      1.91  .0560      -.00298     .23536
HIGH_URB|     -.06608          .07086      -.93  .3511      -.20496     .07281
SUBURBAN|     -.09464          .05848     -1.62  .1056      -.20927     .01998
   RURAL|     -.05436          .06510      -.83  .4038      -.18195     .07324
        |Threshold parameters for index
  Mu(01)|      .40985***       .01955     20.96  .0000       .37153     .44817
  Mu(02)|      .74466***       .02310     32.24  .0000       .69939     .78994
  Mu(03)|     1.16210***       .02759     42.12  .0000      1.10802    1.21618
--------+---------------------------------------------------------------------
--
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
------------------------------------------------------------------------------
--
```

```
+-------------------------------------------------------------------+
|                CELL FREQUENCIES FOR ORDERED CHOICES               |
+-------------------------------------------------------------------+
|               Frequency        Cumulative  < =    Cumulative  > = |
|Outcome       Count    Percent   Count    Percent   Count    Percent |
|----------- ------- ---------  ------- ---------  ------- --------- |
|SDV_U_5=00     708   26.7776      708   26.7776     2644  100.0000 |
|SDV_U_5=01     316   11.9516     1024   38.7292     1936   73.2224 |
|SDV_U_5=02     273   10.3253     1297   49.0545     1620   61.2708 |
|SDV_U_5=03     349   13.2375     1646   62.2920     1347   50.9455 |
|SDV_U_5=04     997   37.7080     2644  100.0000      997   37.7080 |
+-------------------------------------------------------------------+
```

Appendix 5 – Full model 2: AV usage for non-grocery shopping travel

This appendix is an unaltered Nlogit output file. For the meaning of the coded parameters, please refer to the parameter legend of appendix 3 on page 90.

```
|-> SETPANEL ; Group = PAR_ID ; Pds = GR_COUNT $
|-> SKIP $
|-> ORDERED ;
    Lhs=SDV_U_5 ;
    Rhs=one,
    X11_LVL5,X12_TAXI,X21_SF25,X22_SF75,X31_FAST,X32_SLOW,X41_CHP,X42_EXP,
    C_TRAIN,C_BUS,C_BIKE,C_WALK,C_OTHER,C_UNKN,
    C_FREQ,C_TTCAR,C_TTDIFF,C_TCDIFF,
    T_THEMED,T_CENTER,T_LOCAL,
    HAS_CAR,MALE,DR_LCNSE,EDUC_HIG,
    OCC_FTJ,OCC_PTJ,OCC_PTS,
    SIZE_3MR,
    CAR_TINY,CAR_SMAL,CAR_LARG,
    AGE_U30,AGE_4049,AGE_50PL,
    HIGH_URB,SUBURBAN,RURAL,
    ;panel $

----------------------------------------------------------------
Deleted    252 observations with missing data. N is now    4969
----------------------------------------------------------------
+--------------------------------------------------------------------+
| Variable = ____________ Variable Groups    Max     Min     Average |
| GR_COUNT    Group sizes  PAR_ID       730       9       1        6.8 |
+--------------------------------------------------------------------+
+------------------------------------------------------------+
| Frequency count for group sizes of GR_COUNT                |
| Group size =   1    Pct =     .82%    CumPct =     .82%    |
| Group size =   2    Pct =     .96%    CumPct =    1.78%    |
| Group size =   3    Pct =    3.56%    CumPct =    5.34%    |
| Group size =   4    Pct =     .82%    CumPct =    6.16%    |
| Group size =   5    Pct =     .41%    CumPct =    6.58%    |
| Group size =   6    Pct =   58.77%    CumPct =   65.34%    |
| Group size =   7    Pct =     .68%    CumPct =   66.03%    |
| Group size =   8    Pct =    1.23%    CumPct =   67.26%    |
| Group size =   9    Pct =   32.74%    CumPct =  100.00%    |
+------------------------------------------------------------+
Line search at iteration   47 does not improve fn. Exiting optimization.

----------------------------------------------------------------------------
--
Ordered Probability Model
Dependent variable                SDV_U_5
Log likelihood function       -6816.55385
Restricted log likelihood     -7532.48373
Chi squared [   38 d.f.]       1431.85977
Significance level                 .00000
McFadden Pseudo R-squared        .0950457
Estimation based on N =    4969, K =   42
Inf.Cr.AIC  =   13717.1 AIC/N =     2.761
Model estimated: Aug 14, 2017, 22:16:40
Underlying probabilities based on Normal
--------+-------------------------------------------------------------------
--
        |                  Standard            Prob.      95% Confidence
 SDV_U_5|  Coefficient       Error        z    |z|>Z*        Interval
--------+-------------------------------------------------------------------
--
        |Index function for probability
```

Constant	1.24010***	.12870	9.64	.0000	.98785	1.49234
X11_LVL5	.03365	.03940	.85	.3930	-.04356	.11086
X12_TAXI	-.22627***	.03988	-5.67	.0000	-.30444	-.14811
X21_SF25	-.00201	.03927	-.05	.9593	-.07898	.07497
X22_SF75	.26455***	.03950	6.70	.0000	.18712	.34198
X31_FAST	-.03674	.04019	-.91	.3606	-.11552	.04203
X32_SLOW	-.11001***	.03991	-2.76	.0058	-.18823	-.03178
X41_CHP	.04349	.03941	1.10	.2698	-.03375	.12073
X42_EXP	-.28680***	.03957	-7.25	.0000	-.36435	-.20925
C_TRAIN	-.94481***	.09804	-9.64	.0000	-1.13697	-.75266
C_BUS	-.69360***	.08982	-7.72	.0000	-.86964	-.51756
C_BIKE	-1.23029***	.05408	-22.75	.0000	-1.33628	-1.12430
C_WALK	-1.36762***	.07405	-18.47	.0000	-1.51275	-1.22250
C_OTHER	-1.11177***	.18560	-5.99	.0000	-1.47554	-.74801
C_UNKN	-.60360***	.15795	-3.82	.0001	-.91318	-.29402
C_FREQ	.00845	.02887	.29	.7698	-.04814	.06504
C_TTCAR	.00666***	.00106	6.28	.0000	.00458	.00874
C_TTDIFF	-.01074***	.00288	-3.73	.0002	-.01639	-.00510
C_TCDIFF	.00208	.00347	.60	.5494	-.00473	.00888
T_THEMED	.00332	.05511	.06	.9520	-.10469	.11132
T_CENTER	-.07371*	.03872	-1.90	.0570	-.14961	.00219
T_LOCAL	.09776**	.04965	1.97	.0489	.00046	.19507
HAS_CAR	.17383***	.06037	2.88	.0040	.05551	.29216
MALE	.09896***	.03590	2.76	.0058	.02859	.16932
DR_LCNSE	-.12553	.07919	-1.59	.1129	-.28074	.02967
EDUC_HIG	-.06712*	.03488	-1.92	.0543	-.13548	.00124
OCC_FTJ	.05701	.07031	.81	.4175	-.08080	.19482
OCC_PTJ	-.01828	.07637	-.24	.8109	-.16796	.13141
OCC_PTS	.06006	.04032	1.49	.1364	-.01897	.13909
SIZE_3MR	.06901**	.03451	2.00	.0455	.00137	.13666
CAR_TINY	-.02826	.04684	-.60	.5463	-.12006	.06354
CAR_SMAL	-.03628	.04646	-.78	.4349	-.12735	.05479
CAR_LARG	.01736	.05493	.32	.7520	-.09030	.12501
AGE_U30	-.03832	.06391	-.60	.5488	-.16358	.08694
AGE_4049	-.05232	.04451	-1.18	.2398	-.13956	.03492
AGE_50PL	-.15734***	.04321	-3.64	.0003	-.24203	-.07265
HIGH_URB	.04141	.05201	.80	.4259	-.06052	.14335
SUBURBAN	.00794	.04140	.19	.8480	-.07322	.08909
RURAL	-.11848**	.04664	-2.54	.0111	-.20989	-.02706
	Threshold parameters for index					
Mu(01)	.37258***	.01359	27.41	.0000	.34594	.39921
Mu(02)	.77276***	.01664	46.45	.0000	.74015	.80537
Mu(03)	1.28025***	.02044	62.63	.0000	1.24019	1.32031

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

CELL FREQUENCIES FOR ORDERED CHOICES

Outcome	Frequency Count	Frequency Percent	Cumulative < = Count	Cumulative < = Percent	Cumulative > = Count	Cumulative > = Percent
SDV_U_5=00	1272	25.5987	1272	25.5987	4969	100.0000
SDV_U_5=01	547	11.0083	1819	36.6070	3697	74.4013
SDV_U_5=02	630	12.6786	2449	49.2856	3150	63.3930
SDV_U_5=03	806	16.2407	3255	65.5263	2520	50.7144
SDV_U_5=04	1713	34.4737	4969	100.0000	1713	34.4737

Appendix 6 – Full model 3: Change in public transportation (PT) usage for work/education travel

This appendix is an unaltered Nlogit output file. For the meaning of the coded parameters, please refer to the parameter legend of appendix 3 on page 90.

```
|-> SETPANEL ; Group = PAR_ID ; Pds = GR_COUNT $
|-> SKIP $
|-> ORDERED ;
    Lhs=R3_PT ;
    Rhs=one,
    X11_LVL5,X12_TAXI,X21_SF25,X22_SF75,X31_FAST,X32_SLOW,X41_CHP,X42_EXP,
    ACT_FTS,ACT_PTB,ACT_PTS,
    HAS_CAR,MALE,DR_LCNSE,EDUC_HIG,
    OCC_FTJ,OCC_PTJ,OCC_PTS,
    SIZE_3MR,
    AGE_U30,AGE_4049,AGE_50PL,
    HIGH_URB,SUBURBAN,RURAL,
    ;panel $

----------------------------------------------------------------
Deleted   2123 observations with missing data. N is now    575
----------------------------------------------------------------
+--------------------------------------------------------------------+
| Variable = ____________ Variable Groups    Max    Min    Average |
| GR_COUNT   Group sizes  PAR_ID      161      6      1        3.6 |
+--------------------------------------------------------------------+
+---------------------------------------------------------+
| Frequency count for group sizes of GR_COUNT             |
| Group size =   1    Pct =     .62%   CumPct =     .62%  |
| Group size =   2    Pct =     .00%   CumPct =     .62%  |
| Group size =   3    Pct =   79.50%   CumPct =   80.12%  |
| Group size =   4    Pct =     .62%   CumPct =   80.75%  |
| Group size =   5    Pct =     .00%   CumPct =   80.75%  |
| Group size =   6    Pct =   19.25%   CumPct =  100.00%  |
+---------------------------------------------------------+
Normal exit:  30 iterations. Status=0, F=    587.3978

----------------------------------------------------------------------------
--
Ordered Probability Model
Dependent variable                 R3_PT
Log likelihood function       -587.39784
Restricted log likelihood     -618.83845
Chi squared [  25 d.f.]         62.88123
Significance level                .00004
McFadden Pseudo R-squared       .0508059
Estimation based on N =     575, K =  27
Inf.Cr.AIC  =   1228.8 AIC/N =     2.137
Model estimated: Aug 14, 2017, 12:12:25
Underlying probabilities based on Normal
--------+-------------------------------------------------------------------
--
        |                 Standard            Prob.      95% Confidence
   R3_PT|  Coefficient      Error        z    |z|>Z*         Interval
--------+-------------------------------------------------------------------
--
        |Index function for probability
Constant|     .71828*        .41460     1.73  .0832     -.09433   1.53088
X11_LVL5|    -.05211         .11596     -.45  .6532     -.27939    .17517
X12_TAXI|     .01079         .11514      .09  .9253     -.21487    .23646
```

X21_SF25	.09282	.11867	.78	.4341	-.13978	.32541
X22_SF75	.32439***	.11858	2.74	.0062	.09198	.55681
X31_FAST	.05822	.11846	.49	.6231	-.17397	.29040
X32_SLOW	-.05030	.11937	-.42	.6735	-.28426	.18366
X41_CHP	.02565	.11851	.22	.8286	-.20662	.25792
X42_EXP	-.20343*	.11951	-1.70	.0887	-.43766	.03081
ACT_FTS	.03807	.38391	.10	.9210	-.71439	.79053
ACT_PTB	.17769	.43035	.41	.6797	-.66578	1.02117
ACT_PTS	.01461	.15517	.09	.9250	-.28952	.31874
HAS_CAR	.03656	.14203	.26	.7969	-.24181	.31492
MALE	-.38388***	.10270	-3.74	.0002	-.58517	-.18258
DR_LCNSE	-.07890	.19949	-.40	.6925	-.46989	.31208
EDUC_HIG	-.23880**	.11828	-2.02	.0435	-.47063	-.00697
OCC_FTJ	.18394	.32546	.57	.5720	-.45396	.82184
OCC_PTJ	-.13996	.28512	-.49	.6235	-.69878	.41886
OCC_PTS	.14059	.13241	1.06	.2883	-.11892	.40010
SIZE_3MR	-.01754	.11233	-.16	.8759	-.23770	.20263
AGE_U30	-.20066	.15981	-1.26	.2093	-.51389	.11256
AGE_4049	.18068	.13794	1.31	.1903	-.08968	.45104
AGE_50PL	-.13933	.13555	-1.03	.3040	-.40499	.12634
HIGH_URB	-.15544	.14198	-1.09	.2736	-.43372	.12283
SUBURBAN	.07705	.13234	.58	.5604	-.18232	.33643
RURAL	.23293	.15823	1.47	.1410	-.07720	.54305
	Threshold parameters for index					
Mu(01)	1.20698***	.06542	18.45	.0000	1.07875	1.33520

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

CELL FREQUENCIES FOR ORDERED CHOICES

Outcome	Frequency Count	Frequency Percent	Cumulative < = Count	Cumulative < = Percent	Cumulative > = Count	Cumulative > = Percent
R3_PT=00	186	32.3478	186	32.3478	575	100.0000
R3_PT=01	244	42.4348	430	74.7826	389	67.6522
R3_PT=02	145	25.2174	575	100.0000	145	25.2174

Appendix 7 – Full Model 4: Change in bicycle usage for work/education travel

This appendix is an unaltered Nlogit output file. For the meaning of the coded parameters, please refer to the parameter legend of appendix 3 on page 90.

```
|-> SETPANEL ; Group = PAR_ID ; Pds = GR_COUNT $
|-> SKIP $
|-> ORDERED ;
    Lhs=R3_BIKE ;
    Rhs=one,
    X11_LVL5,X12_TAXI,X21_SF25,X22_SF75,X31_FAST,X32_SLOW,X41_CHP,X42_EXP,
    ACT_FTS,ACT_PTB,ACT_PTS,
    C_TTCAR,C_TTDIFF,C_TCDIFF,C_HOMEFQ,
    HAS_CAR,MALE,DR_LCNSE,EDUC_HIG,
    OCC_FTJ,OCC_PTJ,OCC_PTS,
    SIZE_3MR,
    AGE_U30,AGE_4049,AGE_50PL,
    HIGH_URB,SUBURBAN,RURAL
    ;panel $

----------------------------------------------------------------
Deleted   1879 observations with missing data. N is now    819
----------------------------------------------------------------
+-------------------------------------------------------------------+
| Variable = ____________ Variable Groups    Max    Min    Average |
| GR_COUNT   Group sizes  PAR_ID      247      6      1        3.3 |
+-------------------------------------------------------------------+
+-----------------------------------------------------------+
| Frequency count for group sizes of GR_COUNT               |
| Group size =   1   Pct =   2.43%   CumPct =   2.43%       |
| Group size =   2   Pct =   2.02%   CumPct =   4.45%       |
| Group size =   3   Pct =  82.19%   CumPct =  86.64%       |
| Group size =   4   Pct =    .81%   CumPct =  87.45%       |
| Group size =   5   Pct =    .00%   CumPct =  87.45%       |
| Group size =   6   Pct =  12.55%   CumPct = 100.00%       |
+-----------------------------------------------------------+
Normal exit:  36 iterations. Status=0, F=    779.6768

----------------------------------------------------------------------------
--
Ordered Probability Model
Dependent variable               R3_BIKE
Log likelihood function       -779.67684
Restricted log likelihood     -821.69857
Chi squared [  29 d.f.]         84.04346
Significance level                .00000
McFadden Pseudo R-squared       .0511401
Estimation based on N =    819, K =   31
Inf.Cr.AIC  =   1621.4 AIC/N =    1.980
Model estimated: Aug 14, 2017, 12:52:02
Underlying probabilities based on Normal
--------+-------------------------------------------------------------------
--
        |                Standard            Prob.      95% Confidence
 R3_BIKE|  Coefficient      Error       z    |z|>Z*        Interval
--------+-------------------------------------------------------------------
--
        |Index function for probability
Constant|     .49203         .42861     1.15  .2510     -.34802   1.33209
X11_LVL5|     .06578         .10151      .65  .5169     -.13317    .26474
X12_TAXI|     .26908***      .09977     2.70  .0070      .07353    .46462
X21_SF25|    -.05921         .10091     -.59  .5574     -.25700    .13858
X22_SF75|     .12408         .10185     1.22  .2231     -.07555    .32371
```

X31_FAST	.13851	.10321	1.34	.1796	-.06377	.34080
X32_SLOW	-.03942	.10206	-.39	.6993	-.23945	.16061
X41_CHP	.17218*	.10202	1.69	.0915	-.02777	.37213
X42_EXP	-.05551	.10398	-.53	.5934	-.25930	.14828
ACT_FTS	-.94993**	.39879	-2.38	.0172	-1.73153	-.16832
ACT_PTB	-.97258**	.40615	-2.39	.0166	-1.76862	-.17655
ACT_PTS	-.41961*	.22883	-1.83	.0667	-.86811	.02889
C_TTCAR	.00670**	.00296	2.26	.0238	.00089	.01250
C_TTDIFF	-.00734***	.00266	-2.76	.0059	-.01255	-.00212
C_TCDIFF	-.00055	.00479	-.12	.9077	-.00993	.00882
C_HOMEFQ	.09845**	.04196	2.35	.0190	.01621	.18069
HAS_CAR	-.21500*	.12242	-1.76	.0790	-.45494	.02494
MALE	.19312**	.09344	2.07	.0388	.00998	.37626
DR_LCNSE	-.23355	.14946	-1.56	.1181	-.52649	.05939
EDUC_HIG	-.22010**	.10272	-2.14	.0321	-.42142	-.01877
OCC_FTJ	-.49171	.35817	-1.37	.1698	-1.19372	.21029
OCC_PTJ	.33731	.21546	1.57	.1175	-.08499	.75960
OCC_PTS	.24043*	.13797	1.74	.0814	-.02999	.51086
SIZE_3MR	.19383**	.09777	1.98	.0474	.00221	.38546
AGE_U30	.19483	.17186	1.13	.2569	-.14201	.53168
AGE_4049	-.03869	.13594	-.28	.7759	-.30514	.22775
AGE_50PL	.20795*	.12544	1.66	.0974	-.03791	.45380
HIGH_URB	-.29354**	.12151	-2.42	.0157	-.53169	-.05539
SUBURBAN	-.37649***	.11563	-3.26	.0011	-.60311	-.14986
RURAL	.13403	.12361	1.08	.2783	-.10825	.37630
	Threshold parameters for index					
Mu(01)	1.10085***	.05624	19.58	.0000	.99063	1.21108

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

CELL FREQUENCIES FOR ORDERED CHOICES						
	Frequency		Cumulative < =		Cumulative > =	
Outcome	Count	Percent	Count	Percent	Count	Percent
R3_BIKE=00	406	49.5726	406	49.5726	819	100.0000
R3_BIKE=01	287	35.0427	693	84.6154	413	50.4274
R3_BIKE=02	126	15.3846	819	100.0000	126	15.3846

Appendix 8 – Full model 5: Change in bicycle usage for non-grocery shopping travel

This appendix is an unaltered Nlogit output file. For the meaning of the coded parameters, please refer to the parameter legend of appendix 3 on page 90.

```
|-> SETPANEL ; Group = PAR_ID ; Pds = GR_COUNT $
|-> SKIP $
|-> ORDERED ;
    Lhs=R3_BIKE ;
    Rhs=one,
    X11_LVL5,X12_TAXI,X21_SF25,X22_SF75,X31_FAST,X32_SLOW,X41_CHP,X42_EXP,
    C_FREQ,C_TTCAR,C_TTDIFF,C_TCDIFF,
    T_THEMED,T_CENTER,T_LOCAL,
    HAS_CAR,MALE,DR_LCNSE,EDUC_HIG,
    OCC_FTJ,OCC_PTJ,OCC_PTS,
    SIZE_3MR,
    AGE_U30,AGE_4049,AGE_50PL,
    HIGH_URB,SUBURBAN,RURAL
    ;panel $

---------------------------------------------------------------
Deleted    978 observations with missing data. N is now   1720
---------------------------------------------------------------
+-------------------------------------------------------------------+
| Variable = ____________ Variable Groups    Max    Min    Average |
| GR_COUNT   Group sizes  PAR_ID      387      9      1        4.4 |
+-------------------------------------------------------------------+
+-----------------------------------------------------------+
| Frequency count for group sizes of GR_COUNT               |
| Group size =   1   Pct =   1.29%   CumPct =   1.29%       |
| Group size =   2   Pct =   1.29%   CumPct =   2.58%       |
| Group size =   3   Pct =  55.04%   CumPct =  57.62%       |
| Group size =   4   Pct =    .52%   CumPct =  58.14%       |
| Group size =   5   Pct =   1.03%   CumPct =  59.17%       |
| Group size =   6   Pct =  32.82%   CumPct =  91.99%       |
| Group size =   7   Pct =    .26%   CumPct =  92.25%       |
| Group size =   8   Pct =    .26%   CumPct =  92.51%       |
| Group size =   9   Pct =   7.49%   CumPct = 100.00%       |
+-----------------------------------------------------------+
Normal exit:  37 iterations. Status=0, F=    1638.753

---------------------------------------------------------------------------
--
Ordered Probability Model
Dependent variable                 R3_BIKE
Log likelihood function       -1638.75328
Restricted log likelihood     -1697.74402
Chi squared [  29 d.f.]         117.98147
Significance level                 .00000
McFadden Pseudo R-squared        .0347465
Estimation based on N =    1720, K =   31
Inf.Cr.AIC  =   3339.5 AIC/N =    1.942
Model estimated: Aug 14, 2017, 13:02:15
Underlying probabilities based on Normal
--------+------------------------------------------------------------------
--
        |                  Standard            Prob.      95% Confidence
 R3_BIKE|  Coefficient       Error        z    |z|>Z*        Interval
--------+------------------------------------------------------------------
--
        |Index function for probability
Constant|      .08848         .20130      .44   .6603     -.30605    .48302
X11_LVL5|      .10717         .06952     1.54   .1232     -.02908    .24342
```

X12_TAXI	.27552***	.06980	3.95	.0001	.13871	.41233
X21_SF25	-.12696*	.06905	-1.84	.0660	-.26229	.00837
X22_SF75	.12963*	.06877	1.88	.0594	-.00516	.26442
X31_FAST	.08621	.06944	1.24	.2144	-.04989	.22231
X32_SLOW	-.07434	.06991	-1.06	.2877	-.21137	.06269
X41_CHP	.03538	.06860	.52	.6060	-.09908	.16984
X42_EXP	-.18596***	.07024	-2.65	.0081	-.32364	-.04828
C_FREQ	.01409	.04570	.31	.7578	-.07547	.10366
C_TTCAR	.00684***	.00236	2.89	.0038	.00221	.01147
C_TTDIFF	-.01310***	.00465	-2.81	.0049	-.02222	-.00397
C_TCDIFF	.01217*	.00654	1.86	.0628	-.00065	.02499
T_THEMED	.29277**	.12231	2.39	.0167	.05305	.53249
T_CENTER	.00174	.06824	.03	.9797	-.13202	.13549
T_LOCAL	.14877*	.08252	1.80	.0714	-.01297	.31050
HAS_CAR	.06171	.08595	.72	.4728	-.10674	.23016
MALE	.13502**	.06120	2.21	.0274	.01507	.25498
DR_LCNSE	-.27386**	.11596	-2.36	.0182	-.50114	-.04658
EDUC_HIG	-.13898**	.06457	-2.15	.0314	-.26554	-.01243
OCC_FTJ	.07897	.11830	.67	.5044	-.15289	.31084
OCC_PTJ	-.02006	.12380	-.16	.8713	-.26269	.22257
OCC_PTS	.12556*	.07520	1.67	.0950	-.02184	.27295
SIZE_3MR	.13884**	.06212	2.23	.0254	.01708	.26060
AGE_U30	-.11250	.10518	-1.07	.2848	-.31865	.09364
AGE_4049	-.29741***	.08252	-3.60	.0003	-.45915	-.13568
AGE_50PL	-.26700***	.07902	-3.38	.0007	-.42187	-.11213
HIGH_URB	-.13363	.08320	-1.61	.1083	-.29671	.02945
SUBURBAN	.01084	.06991	.16	.8767	-.12617	.14786
RURAL	-.05341	.09625	-.55	.5790	-.24204	.13523
	Threshold parameters for index					
Mu(01)	1.23100***	.04067	30.27	.0000	1.15129	1.31071

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

CELL FREQUENCIES FOR ORDERED CHOICES						
	Frequency		Cumulative < =		Cumulative > =	
Outcome	Count	Percent	Count	Percent	Count	Percent
R3_BIKE=00	819	47.6163	819	47.6163	1720	100.0000
R3_BIKE=01	675	39.2442	1494	86.8605	901	52.3837
R3_BIKE=02	226	13.1395	1720	100.0000	226	13.1395

Appendix 9 – Full model 6: Change travel frequency to work/education destinations

This appendix is an unaltered Nlogit output file. For the meaning of the coded parameters, please refer to the parameter legend of appendix 3 on page 90.

```
|-> SETPANEL ; Group = PAR_ID ; Pds = GR_COUNT $
|-> SKIP $
|-> ORDERED ;
    Lhs=D1_FREQ ;
    Rhs=one,
    X11_LVL5,X12_TAXI,X21_SF25,X22_SF75,X31_FAST,X32_SLOW,X41_CHP,X42_EXP,
    C_TRAIN,C_BUS,C_BIKE,C_WALK,C_OTHER,
    ACT_FTS,ACT_PTB,ACT_PTS,
    C_TTCAR,C_TTDIFF,C_TCDIFF,C_HOMEFQ,
    HAS_CAR,MALE,DR_LCNSE, EDUC_HIG,
    OCC_FTJ,OCC_PTJ,OCC_PTS,
    SIZE_3MR,
    CAR_TINY,CAR_SMAL,CAR_LARG,
    AGE_U30,AGE_4049,AGE_50PL,
    HIGH_URB,SUBURBAN,RURAL,
    ;panel $

---------------------------------------------------------------
Deleted     54 observations with missing data. N is now   2354
---------------------------------------------------------------
+-------------------------------------------------------------------+
| Variable = ____________ Variable Groups    Max    Min    Average |
| GR_COUNT   Group sizes  PAR_ID       674      6      1        3.5 |
+-------------------------------------------------------------------+
+-------------------------------------------------------+
| Frequency count for group sizes of GR_COUNT           |
| Group size =   1   Pct =   4.75%   CumPct =   4.75%   |
| Group size =   2   Pct =   7.42%   CumPct =  12.17%   |
| Group size =   3   Pct =  64.54%   CumPct =  76.71%   |
| Group size =   4   Pct =   1.19%   CumPct =  77.89%   |
| Group size =   5   Pct =   1.34%   CumPct =  79.23%   |
| Group size =   6   Pct =  20.77%   CumPct = 100.00%   |
+-------------------------------------------------------+
Normal exit:  44 iterations. Status=0, F=    1450.859

---------------------------------------------------------------------------
--
Ordered Probability Model
Dependent variable                D1_FREQ
Log likelihood function      -1450.85938
Restricted log likelihood    -1548.00292
Chi squared [  37 d.f.]        194.28710
Significance level               .00000
McFadden Pseudo R-squared       .0627541
Estimation based on N =    2354, K =  39
Inf.Cr.AIC  =   2979.7 AIC/N =     1.266
Model estimated: Aug 14, 2017, 13:18:12
Underlying probabilities based on Normal
--------+------------------------------------------------------------------
--
        |                 Standard            Prob.      95% Confidence
 D1_FREQ|  Coefficient      Error         z    |z|>Z*        Interval
--------+------------------------------------------------------------------
--
        |Index function for probability
Constant|    -.51547**       .25842     -1.99  .0461    -1.02196    -.00898
X11_LVL5|     .03189         .06514       .49  .6245     -.09579     .15956
X12_TAXI|    -.10392         .06561     -1.58  .1132     -.23250     .02467
X21_SF25|    -.08649         .06590     -1.31  .1894     -.21566     .04269
```

```
X22_SF75|    -.14355**       .06567    -2.19  .0288     -.27226   -.01484
X31_FAST|     .18124***      .06638     2.73  .0063      .05113    .31135
X32_SLOW|     .10913         .06676     1.63  .1021     -.02173    .23998
 X41_CHP|     .02185         .06627      .33  .7416     -.10803    .15173
 X42_EXP|     .01957         .06619      .30  .7675     -.11016    .14929
 C_TRAIN|    -.22173*        .11691    -1.90  .0579     -.45088    .00741
   C_BUS|     .34825**       .16923     2.06  .0396      .01657    .67992
  C_BIKE|    -.02054         .09305     -.22  .8253     -.20292    .16183
  C_WALK|     .16336         .29359      .56  .5779     -.41206    .73878
 C_OTHER|     .49267         .42205     1.17  .2431     -.33453   1.31987
 ACT_FTS|    1.21761***      .21817     5.58  .0000      .79001   1.64520
 ACT_PTB|    1.00753***      .23037     4.37  .0000      .55601   1.45904
 ACT_PTS|     .83614***      .09848     8.49  .0000      .64313   1.02915
 C_TTCAR|     .00127         .00132      .96  .3356     -.00132    .00386
C_TTDIFF|     .00413**       .00199     2.08  .0378      .00023    .00804
C_TCDIFF|    -.01769***      .00459    -3.85  .0001     -.02669   -.00869
C_HOMEFQ|    -.00551         .02097     -.26  .7928     -.04662    .03560
 HAS_CAR|     .05475         .10261      .53  .5936     -.14636    .25586
    MALE|     .07366         .06048     1.22  .2232     -.04488    .19220
DR_LCNSE|     .41562***      .13591     3.06  .0022      .14924    .68200
EDUC_HIG|     .13741**       .05946     2.31  .0208      .02086    .25395
 OCC_FTJ|     .82820***      .17829     4.65  .0000      .47875   1.17765
 OCC_PTJ|    -.03963         .16972     -.23  .8154     -.37228    .29302
 OCC_PTS|     .03891         .08130      .48  .6322     -.12043    .19825
SIZE_3MR|     .01356         .05895      .23  .8181     -.10198    .12910
CAR_TINY|    -.01255         .07979     -.16  .8750     -.16892    .14383
CAR_SMAL|     .00712         .08103      .09  .9300     -.15170    .16594
CAR_LARG|     .06719         .09048      .74  .4577     -.11016    .24454
 AGE_U30|     .13871         .11055     1.25  .2096     -.07796    .35537
AGE_4049|     .19844***      .07596     2.61  .0090      .04955    .34732
AGE_50PL|     .23755***      .07310     3.25  .0012      .09427    .38083
HIGH_URB|     .11071         .08426     1.31  .1889     -.05444    .27586
SUBURBAN|    -.06166         .07112     -.87  .3860     -.20104    .07773
   RURAL|    -.07492         .07774     -.96  .3352     -.22729    .07746
        |Threshold parameters for index
  Mu(01)|    2.69165***      .05257    51.20  .0000     2.58862   2.79469
--------+--------------------------------------------------------------------
--
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
--

+---------------------------------------------------------------------+
|                CELL FREQUENCIES FOR ORDERED CHOICES                 |
+---------------------------------------------------------------------+
|               Frequency          Cumulative  < =     Cumulative  > = |
|Outcome     Count    Percent    Count    Percent    Count    Percent |
|----------- ------- ---------  ------- ---------  ------- ---------- |
|D1_FREQ=00      292   12.4044      292   12.4044     2354  100.0000 |
|D1_FREQ=01     1858   78.9295     2150   91.3339     2062   87.5956 |
|D1_FREQ=02      204    8.6661     2354  100.0000      204    8.6661 |
+---------------------------------------------------------------------+
```

Appendix 10 – Full model 7: Change travel frequency to non-grocery shopping destinations

This appendix is an unaltered Nlogit output file. For the meaning of the coded parameters, please refer to the parameter legend of appendix 3 on page 90.

```
|-> SETPANEL ; Group = PAR_ID ; Pds = GR_COUNT $
|-> SKIP $
|-> ORDERED ;
    Lhs=D1_FREQ ;
    Rhs=one,
    X11_LVL5,X12_TAXI,X21_SF25,X22_SF75,X31_FAST,X32_SLOW,X41_CHP,X42_EXP,
    C_TRAIN,C_BUS,C_BIKE,C_WALK,C_OTHER,C_UNKN,
    C_TTCAR,C_TTDIFF,C_TCDIFF,
    T_THEMED,T_CENTER,T_LOCAL,
    HAS_CAR,MALE,DR_LCNSE, EDUC_HIG,
    OCC_FTJ,OCC_PTJ,OCC_PTS,
    SIZE_3MR,
    CAR_TINY,CAR_SMAL,CAR_LARG,
    AGE_U30,AGE_4049,AGE_50PL,
    HIGH_URB,SUBURBAN,RURAL;panel $

---------------------------------------------------------------
Deleted    248 observations with missing data. N is now    5281
---------------------------------------------------------------
+------------------------------------------------------------------+
| Variable = ____________ Variable Groups    Max    Min    Average |
| GR_COUNT   Group sizes  PAR_ID       730     12      1        7.2 |
+------------------------------------------------------------------+
+-------------------------------------------------------+
| Frequency count for group sizes of GR_COUNT           |
| Group size =   1    Pct =    .82%   CumPct =    .82%  |
| Group size =   2    Pct =    .96%   CumPct =   1.78%  |
| Group size =   3    Pct =   3.56%   CumPct =   5.34%  |
| Group size =   4    Pct =    .68%   CumPct =   6.03%  |
| Group size =   5    Pct =    .41%   CumPct =   6.44%  |
| Group size =   6    Pct =  51.78%   CumPct =  58.22%  |
| Group size =   7    Pct =    .82%   CumPct =  59.04%  |
| Group size =   8    Pct =   1.23%   CumPct =  60.27%  |
| Group size =   9    Pct =  32.60%   CumPct =  92.88%  |
| Group size =  10    Pct =    .00%   CumPct =  92.88%  |
| Group size =  11    Pct =    .00%   CumPct =  92.88%  |
| Group size =  12    Pct =   7.12%   CumPct = 100.00%  |
+-------------------------------------------------------+
Normal exit:  43 iterations. Status=0, F=    4341.353

---------------------------------------------------------------------------
--
Ordered Probability Model
Dependent variable              D1_FREQ
Log likelihood function     -4341.35324
Restricted log likelihood   -4481.30048
Chi squared [  37 d.f.]       279.89449
Significance level               .00000
McFadden Pseudo R-squared      .0312292
Estimation based on N =   5281, K =  39
Inf.Cr.AIC  =   8760.7 AIC/N =    1.659
Model estimated: Aug 14, 2017, 13:30:38
Underlying probabilities based on Normal
--------+------------------------------------------------------------------
--
        |                  Standard            Prob.      95% Confidence
 D1_FREQ|  Coefficient       Error       z     |z|>Z*        Interval
```

	Index function for probability					
Constant	.75940***	.12927	5.87	.0000	.50603	1.01277
X11_LVL5	.00299	.03984	.07	.9402	-.07510	.08108
X12_TAXI	-.13143***	.04037	-3.26	.0011	-.21054	-.05231
X21_SF25	-.02621	.04005	-.65	.5128	-.10471	.05228
X22_SF75	.05377	.03978	1.35	.1765	-.02419	.13173
X31_FAST	.07638*	.04034	1.89	.0583	-.00268	.15544
X32_SLOW	.03757	.04027	.93	.3509	-.04137	.11650
X41_CHP	.08412**	.03988	2.11	.0349	.00596	.16229
X42_EXP	-.06294	.04009	-1.57	.1164	-.14151	.01563
C_TRAIN	.13054	.10152	1.29	.1985	-.06843	.32951
C_BUS	-.06370	.09464	-.67	.5009	-.24918	.12179
C_BIKE	-.24474***	.05409	-4.52	.0000	-.35076	-.13872
C_WALK	-.23366***	.07291	-3.20	.0014	-.37657	-.09076
C_OTHER	.06429	.18566	.35	.7291	-.29959	.42818
C_UNKN	.40015***	.08847	4.52	.0000	.22675	.57355
C_TTCAR	.00364***	.00087	4.18	.0000	.00193	.00535
C_TTDIFF	-.00291	.00224	-1.30	.1938	-.00729	.00148
C_TCDIFF	-.00330	.00307	-1.07	.2827	-.00932	.00272
T_THEMED	-.08267	.05407	-1.53	.1263	-.18865	.02331
T_CENTER	-.04494	.03917	-1.15	.2513	-.12171	.03184
T_LOCAL	-.25544***	.05017	-5.09	.0000	-.35378	-.15711
HAS_CAR	-.22471***	.06122	-3.67	.0002	-.34471	-.10472
MALE	-.17010***	.03656	-4.65	.0000	-.24176	-.09844
DR_LCNSE	.14872*	.07936	1.87	.0609	-.00682	.30427
EDUC_HIG	.10003***	.03511	2.85	.0044	.03123	.16884
OCC_FTJ	.08755	.07223	1.21	.2254	-.05401	.22911
OCC_PTJ	.05554	.07856	.71	.4795	-.09843	.20952
OCC_PTS	.10163**	.04048	2.51	.0121	.02229	.18097
SIZE_3MR	.01519	.03508	.43	.6650	-.05357	.08395
CAR_TINY	.10404**	.04811	2.16	.0306	.00974	.19834
CAR_SMAL	.04592	.04722	.97	.3309	-.04664	.13848
CAR_LARG	.00610	.05538	.11	.9123	-.10244	.11463
AGE_U30	.20638***	.06562	3.15	.0017	.07777	.33499
AGE_4049	.11612***	.04478	2.59	.0095	.02836	.20388
AGE_50PL	.08928**	.04361	2.05	.0406	.00381	.17475
HIGH_URB	.17914***	.05247	3.41	.0006	.07631	.28198
SUBURBAN	.13661***	.04232	3.23	.0012	.05366	.21956
RURAL	-.01396	.04712	-.30	.7670	-.10632	.07839
	Threshold parameters for index					
Mu(01)	2.06095***	.02785	73.99	.0000	2.00636	2.11555

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

CELL FREQUENCIES FOR ORDERED CHOICES

Outcome	Frequency Count	Frequency Percent	Cumulative < = Count	Cumulative < = Percent	Cumulative > = Count	Cumulative > = Percent
D1_FREQ=00	985	18.6518	985	18.6518	5281	100.0000
D1_FREQ=01	3577	67.7334	4562	86.3852	4296	81.3482
D1_FREQ=02	719	13.6148	5281	100.0000	719	13.6148

Appendix 11 – Full model 8: Change in average trip length of non-grocery shopping trips

This appendix is an unaltered Nlogit output file. For the meaning of the coded parameters, please refer to the parameter legend of appendix 3 on page 90.

```
|-> SKIP $
|-> ORDERED ;
    Lhs=D1_AVGT ;
    Rhs=one,X11,X12,X21,X22,X31,X32,X41,X42,
    CARPOS,OCC_FTB,OCC_FTS,OCC_PTB,OCC_PTS,MALE,
    HHS_3M,STUDHOUS,C_MICO,C_SMMI,C_LATO,
    U30,A4050,A50M,HIGHER,DRLICEN,HIGHURB,SUBURB,RURAL
    $

----------------------------------------------------------------
Deleted      27 observations with missing data. N is now    2220
----------------------------------------------------------------
Line search at iteration    35 does not improve fn. Exiting optimization.

---------------------------------------------------------------------------
--
Ordered Probability Model
Dependent variable               D1_AVGT
Log likelihood function      -2071.15566
Restricted log likelihood    -2096.85415
Chi squared [   27 d.f.]        51.39697
Significance level                .00313
McFadden Pseudo R-squared       .0122557
Estimation based on N =    2220, K =   29
Inf.Cr.AIC   =    4200.3 AIC/N =    1.892
Model estimated: Aug 12, 2017, 12:56:12
Underlying probabilities based on Normal
--------+------------------------------------------------------------------
--
        |                  Standard            Prob.       95% Confidence
 D1_AVGT|  Coefficient       Error       z    |z|>Z*         Interval
--------+------------------------------------------------------------------
--
        |Index function for probability
Constant|      .98268***      .19008     5.17  .0000      .61014   1.35523
     X11|     -.03335         .05900     -.57  .5718     -.14899    .08228
     X12|     -.10267*        .05902    -1.74  .0820     -.21835    .01302
     X21|      .03107         .05915      .53  .5994     -.08487    .14700
     X22|      .10560*        .05933     1.78  .0751     -.01069    .22188
     X31|      .10115*        .05931     1.71  .0881     -.01509    .21740
     X32|      .10300*        .05938     1.73  .0828     -.01338    .21937
     X41|      .12357**       .05938     2.08  .0374      .00720    .23995
     X42|     -.02110         .05929     -.36  .7219     -.13730    .09510
  CARPOS|     -.19518**       .09122    -2.14  .0324     -.37397   -.01638
 OCC_FTB|      .00519         .12110      .04  .9658     -.23217    .24254
 OCC_FTS|      .14716         .13661     1.08  .2814     -.12058    .41491
 OCC_PTB|     -.15489         .11671    -1.33  .1844     -.38363    .07384
 OCC_PTS|     -.01844         .06338     -.29  .7712     -.14266    .10579
    MALE|     -.02160         .05500     -.39  .6946     -.12941    .08621
  HHS_3M|      .02032         .05261      .39  .6994     -.08280    .12343
STUDHOUS|     -.00367         .13524     -.03  .9783     -.26873    .26139
  C_MICO|      .18691***      .07071     2.64  .0082      .04832    .32551
  C_SMMI|      .07666         .06993     1.10  .2729     -.06039    .21372
  C_LATO|      .02168         .08290      .26  .7937     -.14079    .18415
     U30|     -.05296         .10947     -.48  .6285     -.26752    .16159
   A4050|      .17320**       .06789     2.55  .0107      .04014    .30627
    A50M|      .12197*        .06534     1.87  .0620     -.00610    .25003
  HIGHER|     -.05594         .05232    -1.07  .2850     -.15849    .04661
```

DRLICEN	-.17687	.11756	-1.50	.1325	-.40729	.05355
HIGHURB	.15155*	.07786	1.95	.0516	-.00104	.30415
SUBURB	.08959	.06252	1.43	.1519	-.03294	.21212
RURAL	-.00187	.06851	-.03	.9782	-.13616	.13241
	Threshold parameters for index					
Mu(01)	1.72678***	.03804	45.39	.0000	1.65222	1.80135

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

CELL FREQUENCIES FOR ORDERED CHOICES

	Frequency		Cumulative < =		Cumulative > =	
Outcome	Count	Percent	Count	Percent	Count	Percent
D1_AVGT=00	423	19.0541	423	19.0541	2220	100.0000
D1_AVGT=01	1343	60.4955	1766	79.5495	1797	80.9459
D1_AVGT=02	454	20.4505	2220	100.0000	454	20.4505