MASTER

Vehicle users' preferences concerning automated driving implications for transportation and market planning

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Vehicle Users' Preferences Concerning Automated Driving

Implications for Transportation and Market Planning

by

I.C.H.M. Megens

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Colophon

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Management summary

The everlasting demand for mobility has led to three key challenges: the daily occurrence of traffic accidents, a dense road network that often results in long traffic jams, and emissions that pollute the environment. A next step in the evolution of technology to aid society is the introduction of automated driving for passenger vehicles. To benefit from the technology, widespread user support is required. To use automated driving systems, vehicle users have to release control. However, literature indicates that this is a very critical point.

Vehicle users trust themselves more in carrying out the control function, than they trust automated technology in doing this. Therefore, this thesis aims to gain insights for which level of automation and in which driving circumstances, vehicle users are willing to release driving control. With this insights, recommendations concerning market and transportation plans can be given as it forecasts in which driving situations most support for automated driving is expected.

Five levels of automation are distinguished by BASt expert group. These levels go from no active driving control by automated systems, to carrying out full driving control by automated systems. The five levels are labeled as: driver only, assisted driving, partial automation, high automation, and full automation. Driving circumstances, including associated levels, that are taken in account in the research are:

- Road type: highway, regional road, local road
- Density of traffic on the road: low, average, high
- Length of the trip: < 20 km, 20-100 km, > 100 km
- Familiarity with the route: familiar, unfamiliar
- Secondary task: yes, no

By a discrete choice experiment it is described which level of automation and which driving circumstances contribute to the willingness of vehicle users to release driving control. These are:

- Assisted driving or partial automation;
- Highways;
- Familiar route;
- Not performing a secondary task.

The results indicate that most vehicle users are not yet willing to use fully automated systems. However, although small, there is a group that is willing to release all control. This group can grow when developments around automated driving mature. The following recommendations are stressed concerning the transportation planning. First focus to successfully implement automated driving should be on creating strong collaborations and feasibility studies for automation on highways. Eventually public parties should aim at also enabling automated driving on regional roads, because this could offer very high safety benefit levels. Furthermore, it is recommended to enable automated driving on dense roads. Along these lines, benefits for society are highest. Lastly, it is recommended to be careful with enabling high automated driving. Although very less attention from vehicle users is required, small human errors could lead to fatal accidents.

Acknowledgments

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Additionally, I would express my gratitude to my friends for their support. Especially Maud, Han and Stefanie who provided me with feedback on this thesis. Personal recognition goes out to my parents and sister for their support during my studies.

Interest in the subject of this thesis has grown on me. I enjoyed writing my master's thesis and hope you will enjoy reading it.

Ilse Megens,
Eindhoven, 2014

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List of abbreviations

ACC	Adaptive Cruise Control
ETW	Erftoegangsweg (Dutch), referred to as 'local road'
GOW	Gebiedsontsluitingsweg (Dutch), referred to as 'regional road'
ITS	Intelligent Transportation Systems
LC model	Latent class model
ML model	Mixed logit model
MNL model	Multinomial logit model
SW	Stroomweg (Dutch), referred to as 'highway'

Chapter 1

Introduction

Passenger vehicle mobility enables daily activities of businesses and consumers. It therefore provides a valuable contribution to welfare in the Netherlands. It provides economic and personal growth along with the experience of freedom. However, mobility has also exposed society to some dangers. Traffic accidents occur on daily basis, the dense road network often leads to long traffic jams, and emissions are polluting the environment. These dangers are the result of the everlasting demand for mobility, leading to several key societal challenges (Kennisinstituut voor Mobiliteitsbeleid, 2013; Ministry of Transport, Public Works and Water Management, 2005).

1.1 Societal challenges concerning passenger vehicle mobility

The first challenge is the search for safer transportation possibilities. Every year accidents costs Dutch society around 12,5 billion euro. In 2009, these costs represented 2,2% of the gross domestic product (Kennisinstituut voor Mobiliteitsbeleid, 2013). Motorized vehicles have a high share in this. They are involved in almost half of the traffic accidents (Norden & Bijleveld, 2011). SWOV, an institute for road safety research has found that most of the traffic accidents occur due to driver error, such as driver's fatigue, the loss of the driver's attention or are related to substance abuse of alcohol and drugs (SWOV, 2011; 2012a; 2012d). Other factors involve speeding, aggressive driving, over-compensation, inexperience, slow reaction times, and various other human driving shortcomings (Fagnant & Kockelman, 2014). Luckily, over the last years the number of traffic causalities has strongly decreased. In 2013 this resulted in 570 traffic causalities, of which more than one-third traveled by passenger vehicle (CBS, 2014). According to the Kennisinstituut voor Mobiliteitsbeleid (KiM), a Dutch institute for transport policy analysis (2013), the decreasing number can be partly attributed to the application of airbags, cruise control, Antilock Braking System and other comparable systems. Still, every fatal traffic causality is one too many and therefore, further use of technology developments could have even more safety benefits.

The second challenge is to improve the traffic flow. According to KiM, the total travel time on Dutch main road network keeps on growing. The reason for the rise is twofold: the distance drivers travel, as well as the amount of vehicles on the road is increasing. Negative effects of these developments are the increased congestion and delayed traffic flow. Congestion has cost society between 1,8 and 2,4 billion euro in 2009, of which more than two-third is on account of passenger driving. To lower the negative effects, measures such as additional lanes and better traffic management are implemented (Kennisinstituut voor Mobiliteitsbeleid, 2013). However, the effects of the current policy measures lag with the increasing need for mobility. Without taking effective measures, traffic flow on Dutch roads will worsen and the roads will clog up (Raad voor Verkeer en Waterstaat, 2007).

The third challenge concerns the world's climate change. Vehicles emit greenhouse gasses, especially air pollution and CO_2. Air pollution has a negative influence on people's health and causes damage to nature, agriculture crops and buildings (Kennisinstituut voor Mobiliteitsbeleid, 2013). This results in societal welfare loss. CO_2 emission of traffic is connected to energy use and therefore a measurement of environmental savings. Traffic accounts for one-fifth on the total CO_2 emissions in the Netherlands, of which more than half of the CO_2 emission is caused by passenger vehicles. In 2012, the costs of CO_2 and air pollution by traffic were around 5,1 billion euro, one-fourth less than in 2000 (Kennisinstituut voor Mobiliteitsbeleid, 2013). This reduction is in line with the aim of the European Union to stabilize climate change by reducing greenhouse gas emissions and saving primary energy (European Parliament and the Council of the European Union, 2009). However, to achieve this goal, a structural decline of CO_2 emission of passenger vehicles is required (Kennisinstituut voor Mobiliteitsbeleid, 2013; Atsma, 2011).

1.2 Technological solution

The above-mentioned issues expose society to health risks and result in financial costs. Moreover, the road network in Netherlands is clogging up which leads to a reduction of welfare. In recent years, different platforms, such as Nederland Innovatief Onderweg and Connected Mobility, have recognized the effects of Intelligent Transportation Systems as beneficial to these societal challenges. Intelligent Transportation Systems (ITS) are usually seen as information and communication technologies that are applied within vehicles as well as within the driving environment. ITS enable a flexible and dynamic traffic system, adapted to up to date situations (SWOV, 2010b). Although ITS have a low usage rate and are only purchased in vehicles in high-end segments, vehicle manufacturers are working on a next step of technology to aid society: an automated driving experience in which systems take over driving control (of driving tasks) from humans (Arem, 2013; Zwaneveld & Arem, 1997). Automated driving should improve safety, traffic flow and increase environmental savings. Driving control can be taken over to varying degrees, which is reflected by different levels of automation. With a higher level of automation, more control of is released from vehicle users to automated systems. The introduction of automated driving changes the control that is performed by vehicle users while driving, and thus creates a new role division for vehicle users, the vehicle and its driving environment. However, it is not granted that vehicle users want to adjust their current role, as they are not always eager to release control (Muir, 1987). The willingness of drivers to release driving control to automated systems is thus critical to the success of automated driving (SWOV, 2010b; KPMG & CAR, 2012; Driel & Arem, 2005).

While driving, safety-critical tasks, such as steering clear of other vehicles, must be performed. However, vehicle users seem to trust themselves more in correctly carrying out the control than they trust automated systems in doing this (Lee & Moray, 1994). The control that should be carried out by humans depend on the level of automation and the driving circumstances, and therefore determine the vehicle user's interaction with the vehicle and driving environment. The new role of the vehicle user in the driving situation can alter this interaction and therefore can lead to changes in vehicle users' preferences concerning driving (Saad, 2006). This is acknowledge by previous research concerning ITS. For example, euroFOT research has indicated that systems that take braking and accelerating tasks are perceived as more useful on highways than on rural roads. In addition, the same systems are perceived as more useful on highways with heavy traffic than on highways with light traffic. In addition, the same systems are perceived as more useful on highways than on rural roads (Sanchez, et al., 2012). Besides, previous research has indicated that preference concerning automated driving also differ per user group (KPMG, 2013).

Hence, the vehicle user's preferences regarding the driving circumstances and the level of automation, determine if the vehicle user wants to release driving control. It is assumed that the more the implementation plans of automated driving are aligned with the preferences of vehicle users, the higher the support for automated driving. Support is a precondition that will permit the automated driving to achieve their potential societal benefit levels (Adell, 2010).

1.3 Research questions

Implementation plans concerning automated driving are in exploration phase. However, Literature lacks insights in the preferences of vehicle users concerning automated driving in different driving circumstances. The research described in this thesis sets out to breach this gap and therefore aims to answer the following main question:

> *Which level of automation and which driving circumstances contribute to the willingness of different vehicle user groups to release driving control?*

To support the main question, four sub-questions are defined:

> *What is automated driving and what are current and expected technological capabilities?*
>
> *What are the benefits of automated driving for society, regarding safety, traffic flow and environmental savings?*
>
> *How do the level of automation and driving circumstances determine usage rate of automated driving systems?*
>
> *What are the preferences concerning automated driving for different user groups?*

Answering these questions firstly results in more theoretical insights in the preferences of vehicle users concerning road transportation innovations. Secondly, it offers insight in the perception of vehicle users to release driving control in different driving situations, which accordingly provides managerial guidelines for successful implementation. Transportation and market planners can take measures that are in accordance with preferences of vehicle-users and hence maximize the potential benefits of automated driving.

1.4 Research method

Information processed in this thesis is obtained from literature research and from a discrete choice experiment. On account of the found literature, a questionnaire with closed questions is set up to gain data for the discrete choice experiment. The experiment involves three choice models that describe the willingness of vehicle users to cede driving tasks in different driving situations. The models which are applied are: Multinomial logit model, Latent class model, and Mixed logit model.

1.5 Scope

This thesis involves passenger driving in the Netherlands. It does not involve freight traffic as the circumstances and aims of driving are totally different (Houses of Parliament, 2013). Nor does it involve automated parking, as this does not considerably contribute to safety, traffic flow and environmental savings. Furthermore, the thesis provides only insights in which implementation plans could benefit effects for society. According to Adell (2010), societal and individual benefits do not necessarily coincide and therefore are not taken in account. In addition, it will not describe how individual motives such as costs, liability and privacy, influence automated driving acceptance. It will only focus on the willingness to release control.

For two main reasons it is interesting to focus this research on the Netherlands. First, Dutch society is dealing with very dense traffic conditions. Implementing automated driving on Dutch roads can majorly increase the economic welfare and the livability. Secondly, the Dutch Secretary of Infrastructure and Environment wants to have a leading role in implementation of automated driving. In the coming years, Dutch roads will be available for test drives and the Secretary seems to target at a high usage rate (Secretary Schultz van Haegen, 2014).

1.6 Outline

This thesis consists of 8 chapters, in which the research questions as formulated in the introduction will be answered. The outline is depict in
Figure 1.1.

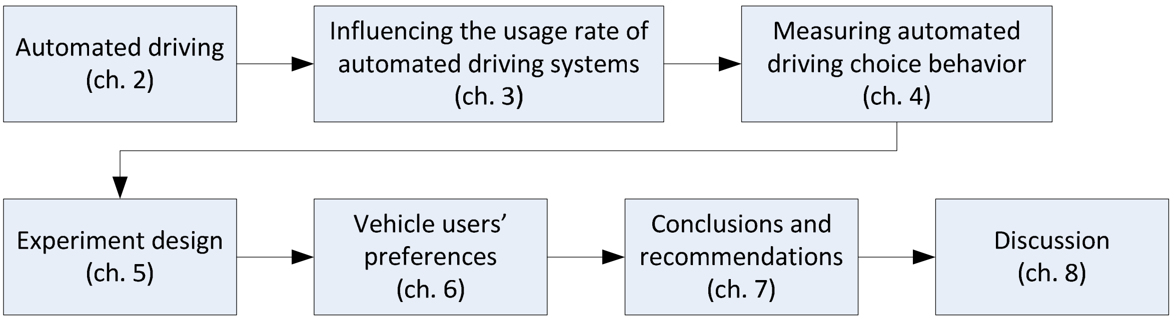


Figure 1.1: Thesis outline

Chapter 2 gives a theoretical overview about the topic automated driving and thereby aims at answering the first two sub-questions. With this background knowledge, Chapter 3 presents driving circumstances that influence the willingness to release driving control and provides insights in how the usage rate of automated systems is influenced, and thereby aims to answer the third sub-question. Next, Chapter 4 describes how preferred driving circumstances and level of released tasks can be measured by modeling choice behavior. Subsequently, Chapter 5 provides insights how an experiment is designed to attain data to model choice behavior. In Chapter 6, data is analyzed and modeled choice behavior of vehicle users is described. This provides insights in automated driving preferences of different user groups. Chapter 7 answers the main research question with support of concise answers on the sub-questions. Furthermore, it will provide managerial recommendations for stakeholders. In Chapter 8, the results will be discussed.

Chapter 2

Automated driving

Since almost a century, planners, engineers, and visionaries are involved in the quest to enable people to travel in passenger vehicles without being constantly attentive . This quest seems to come to an end as several vehicle manufacturers have said that they are close to making automated driving reality (Autoblog, 2013; Weber, 2014). In Section 2.1, history of the quest for automated driving is concisely explained. Next, Section 2.2 discusses the technological developments around automated driving. Thereafter, Section 2.3 explains what the main benefits for society could be if vehicle manufacturers succeed in their goal to enable fully automated driving. Further, the implementation plans of policy makers and additional implementation challenges of automated driving are explained in Section 2.4. To summarize, Section 2.5 captures the main points from the previous sections.

2.1 History of automated driving

After manually driven vehicles took over traveling possibilities from horse-drawn wagons, a new experience of driving was constituted (Hayes, 2011). This experience involved a mix of anxiety, alertness, and boredom, which resulted in the dream for self-driven vehicles which could rule out these negative states of mind (Weber, 2014). In 1939 at the General Motors Futurama exhibit, planners would image that in 1960 vehicles would drive at a safe distance through automatic radio control on dedicated automated tracks[1]. By the 1960's, sensing and reacting with an appropriate movement was feasible. However, how to process and deal with the outside world was still unknown (Weber, 2014). Again, several new predictions were made which implied that automated vehicles would be on public roads within 15 to 25 year. Once more, this prediction was not correct. But later on, around the mid-1980s, several driverless-systems were designed and tested which resulted in vehicles with automated functionalities (Anderson, et al., 2014).

In the last 25 years, three development phases can be identified. Firstly, between 1980 and 2003, two main technology concepts emerged. The first concept was the development of automated highway systems, in which vehicles where guided by the highway infrastructure. As a second technology concept, semi-automated vehicles were developed that could in steer or navigate by automation in several circumstances. Successively, from 2003 to 2008, the U.S. Defense Advanced Research Projects Administration (DARPA) Grand Challenges were held. The challenge was to automatically navigate vehicles over a course that ran across a desert. DARPA's purpose was to accelerate technological developments of automated vehicles which could ultimately substitute humans in hazardous military operations. In the first years, the vehicles of research teams failed miserably and traveled only a few miles before they crashed. But some years later, successes extended from desert

[1] *The City - American Insititude of City Planners, 1939*, https://www.youtube.com/watch?v=7sic-Q_weok

driving to a mock city environment. This markedly accelerated advancements in automated vehicle technology (Anderson, et al., 2014).

In the last years, major technology steps are taken. Firstly, there are some mobiles that can fully drive themselves. However, they are restricted by the fact that they can only drive in very limited driving situations, such as closed environments with a really low top speed (Weber, 2014). Secondly, most well-known vehicle manufacturers are currently working on fully automated vehicles (Fagnant & Kockelman, 2014). In April 2014, Google's vehicles have logged nearly 700.000 miles, more than one million kilometers (Urmson, 2014). Examples of other manufacturers that started test drives are Audi, BWM, Nissan, Volvo, Lexus, Tesla and Mercedes (Autoblog, 2013). Most of these manufacturers already had experience with automated systems as they have several ITS on the market.

2.2 Technological developments

The technology behind automated driving depends on three factors. Firstly, In-car systems provide the driver with information, for example about traffic congestion or weather circumstances. Secondly, Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I) and Infrastructure to Infrastructure (I2I) applications provide the ability to communicate with each other and take action accordingly. For example, when the brakes are pushed, this information will be communicated to vehicles in the vicinity. In response, these will take action to maintain a safe distance. Thirdly, autonomous systems are incorporated which independently respond to situations. For example, when a sensor of the vehicle notices another object in its near environment, it will act accordingly. Hence, the difference between cooperate and autonomous working systems is that the first responds to information of other vehicles, while the second responds to the situation. Together, the three abilities will form the basis of a fully automated vehicle (National Highway Traffic Safety Administration, 2013; Timmer, et al., 2013; Wilmink & Schuurman, 2014).

In literature, often the terms 'autonomous' and 'automated' are used to describe the vehicle that is not fully human-driven. The difference between those terms is that autonomous refers to the vehicle being operated independently or by itself on basis of own sensors, while automated refers to the vehicle being operated by a machine by using communication as well as own sensors (DITCM, 2014). In this thesis the term 'automated driving' is used as this is deployed more often in professional environments. Automated driving refers to the vehicle as well as the road based infrastructure.

Automated technology enables vehicles to partly or fully drive themselves by taking over control from humans. If a vehicle does not perform a control function, but provides warnings or information, it is not considered as automated. Human-driven vehicles could ultimately be replaced by vehicles that do not require a driver anymore (Anderson, et al., 2014).

In the next three subsections will provide more information about respectively the types of driving tasks, the levels of automation, and available systems.

2.2.1 Driving tasks

Automated driving differs from manual driving as the technology behind the vehicle and road infrastructure executes the driving tasks (KPMG, 2013). The performance of the automation can be divided in primary, secondary and tertiary driving tasks. Primary tasks include control over steering, accelerating, braking, choosing the right lane, speed, route, and distance to other vehicles. Secondary tasks include over dimming, operating windscreen wipers, coupling, changing gears and blinking. Both primary and secondary tasks are mainly safety related, while tertiary tasks, which include activities like operating air conditioner, seat heater, radio and phone, are more comfort-related (Eyben, et al., 2010).

2.2.2 Levels of automation

Collaborating Intelligent Transportation Systems together form a continuum from vehicles with no active control to vehicles which have fully automated control. Different organizations have provided a categorization of the levels of automation: Bundesanstalt für Straßenwesen (BASt) expert group, National Highway Traffic Safety Administration (NHTSA), and SAE International. The analogy between these categorizations is very high. The main difference is that BASt expert group did not include a level for driverless vehicles, while NHTSA and SAE International do. The analogy between the levels of the different categorizations are presented in Appendix I. This thesis will use the BASt expert group labels as these labels are also very understandable for non-experts in the field of automated driving. The labels are described in Table 2.1.

Table 2.1: Levels on automation, indicated by BASt expert group (Gasser, et al., 2013)

Levels of automation	Role-divsion of driver and system	
Driver only	The driver continuously (throughout the complete trip) accomplishes longitudinal (accelerating/ braking) and lateral (steering) control.	
Assisted	The driver continuously accomplishes either lateral or longitudinal control. The other/remaining task is – within certain limits - performed by the system. • The driver must monitor the system permanently. • The driver must be prepared to take over complete control over the vehicle at any time.	
Partial automation	The system takes over the lateral and longitudinal control (for a certain period of time and/or in specific situations). • The driver must monitor the system permanently. • The driver must be prepared to take over the complete control of the vehicle at any time.	

High automation	The system takes over lateral and longitudinal control for a certain period of time in specific situations. • Here, the driver need not monitor the system permanently. • If necessary, the driver will be prompted to take over control, allowing for a sufficient lead time. • All system limits are recognized by the system. The system is not capable of re-establishing the minimal risk condition from every initial state.	
Full automation	The system takes over lateral and longitudinal control completely within the specification of the application. • The driver need not monitor the system. • Before specified limits of the application are reached, the system prompts the driver to take over control, with sufficient lead time. • In absence of driver takeover, the system will return to the minimal risk condition. • All system limits are recognized by the system. The system is capable of returning to the minimal risk condition out of every situation.	

2.2.3 Available systems

Automated driving systems use information that comes from sensors, radars, scanners, cameras, GPS, telecommunication, and maps. The automated vehicle itself works also as an important sensor within the network. With information exchange, consequences of weather, density on the road, braking movements and lane changes of other vehicle users can be monitored (Timmer, et al., 2013). An example of how an automated vehicle captures environmental information is shown in Figure 2.1.

Figure 2.1: data captured by the technology of Google's automated vehicle (Knight, 2013)

There are several ITS on the market that can take over control of driving tasks. The system-names, which numerous vehicle manufacturers use, are often different, but incorporate the same functionalities. Currently, ITS on the market only take over control one driving task or two collaborative driving tasks. Therefore, only assisted and partial automation is currently on the market. The different systems are often designed to operate on definite road types. For example, standard Adaptive Cruise Control-systems only operate with speeds above 30 km/h (SWOV, 2010a). An overview of the functionalities made by Working Group Automation in Road Transport (2013) is shown in Appendix II. Well-known systems that take over manual control of driving tasks are (Fagnant & Kockelman, 2014; Mercedes-Benz, n.d.; Özgüner, et al., 2007):

- (Cooperative) Adaptive cruise control - allows automated braking and accelerating;
- Pre crash system - allows automated emergency braking;
- Automatic parking system - allows automated steering;
- Lane-keeping system - allows the vehicle to maintain between road lanes;
- Stop and go system - including an automated steering system it allows automated congestion driving.

Current technology for highly automated driving in controlled environments is quite mature (Working Group Automation in Road Transport, 2013). Tests have been executed with highly automated vehicles driving on urban and in highway environments by vehicle manufacturers such as Google, Mercedes-Benz, BMW, NISSAN and General Motors (Google Blog: Chris Urmson, 2014; Mercedes-Benz, n.d.; Volvo Cars, 2014; Knight, 2013). Volvo, for example, will bring hundred automated test vehicles on a 50 km long lane Sweden. However, no high or fully automated vehicle that is so well tuned that it can be available for public is on the market yet. Usage of a combination of Adaptive Cruise Control, Lane Keeping and Driver Monitoring, comes closest to automated driving.

2.3 Implications for society

Assuming that the technology for automated vehicles matures and will be successfully implemented, entering the mass user market can have major implications for the mobility system. Increase of traffic safety, improvement of traffic flow and environmental savings are often mentioned positive effects. But also other effects may have high influence on society. Table 2.2 shows an overview of the expected strengths, weaknesses, opportunities and threats of full automated driving that can be found in literature (e.g. Fagant & Kockelman, 2014; KPMG & CAR, 2012; Litman, 2014). Many of these implications are interrelated and interdependent; some of the implications can be directly observed while others are indirectly present.

Impacts like reduced driver stress and increased roadway capacity will occur when partial or high automated driving is deployed. However, most impacts will only be recognized when full automation is used by the critical user mass (Litman, 2014). Examples are reduction of congestion and accidents (Litman, 2014). It should be taken in account that on longer term, the use of automated driving could have effect on issues that are currently not measurable. Examples are a loss of driving skills, a reduction of attention level and an increase of the attraction of using highways (Rijkswaterstaat, 2007).

Table 2.2: Implications of automated driving

Strengths	Weaknesses
- Fuel savings - Averted (deadly) crashes - Reduction of stress level for vehicle users - Possibility to rest or work while travelling - Reduction of traffic congestion - Efficient parking - Increased road capacity	- Reduced employment and business activity - Increased ownership costs because of vehicle equipment etc.
Opportunities	**Threats**
- Independent mobility for elderly and disabled - New models for vehicle ownership and vehicle sharing - Travel time dependability - New business models and scenarios	- Data challenges - Technology failure - Liability, licensing, and insurance concerns - Security and privacy concerns - Too much additional vehicle traffic because of experienced comfort - Social equity concerns, unfair impacts - Misplaced planning emphasis - Poor Human-Machine interaction

The automotive industry and many researchers have focused on models, simulations and field operational tests (FOT) to give an quantitative indication of the effects of public usage of automated driving. However, it appears to be hard to give an empirical prove of its effectiveness as the automated driving system is very complex (Timmer, et al., 2013). Accurate estimations of the effects of automated driving are not yet available. Besides, ITS that are currently on the market tend to have a low usage rate and thus cannot prove much empirical evident of the implications automated driving could have (Arem, 2013; Malone, 2008). However, although most results are only based on assumptions, or are based on assisted driving, they can give an indication of effects. Therefore, most implications addressed below are qualitative of nature, very basic or only based on independently working systems. At least the same performance indications as with independently working systems are assumed to be reached for automated driving as automated vehicles and environment also incorporate these or similar working systems.

The next three subsections will further pay attention to most recognized implications for automated driving. These effects are also the main challenges for the passenger vehicle mobility system, as explained in Chapter 1.

2.3.1 Safety

The first main positive effect is increased traffic safety. When the technology for automated driving is matured, they could detect and neutralize safety-critical driving events more adequately than human drivers. They prevent unsafe traffic participation, unsafe actions during traffic participation, and reduce the impact of accidents (SWOV, 2010b).

According to Secretary Schultz van Haegen (2014) of the Ministry of Infrastructure and Environment, 90% of the accidents occur due to human errors. Therefore, the scope of potential benefits of using automated driving is substantial. Hayes (2011) suggests that fatality rates could eventually approach similar results as seen in aviation and rail, which is one percent of the current rate. TNO and around 20 IT and Infrastructure companies, which are united in Nederland Innovatief Onderweg (2010), have made some predictions of effects of several transportation systems in the Netherlands. They estimate that the amount of deadly accidents can be declined with 25 to 50%, depending on the level of compulsion of the system. In another research of TNO it is predicted that there will be 25% less road fatalities when Intelligent transportation Systems will work together (Arem, et al., 2008).

The potential total safety contribution of driving automated depends on the driving situation. Most accidents in the Netherlands occur on "gebiedsonsluitendewegen" (GOW), further referred as regional roads (Figure 2.0.2). These roads are limited obstacle free, while driving with a high speed is enabled (Davidse, 2012). In addition, many accidents happen on "erftoegangswegen" (ETW), further referred to as local roads. The least number of accidents occur on "stroomwegen" (SW), further referred to as highways (Rijkswaterstaat, 2007). Mesken (2012) found a positive relation between density on the road and the number of accidents. Also weather circumstances have different effect on traffic safety. Therefore, assumed that technology could diminish all human errors, the reduction of accidents is highest when vehicle-users release driving control on dense regional roads. However, the actual effects depend on the exact actions of the system, the penetration rate and the possible unintended side effects (SWOV, 2010b).

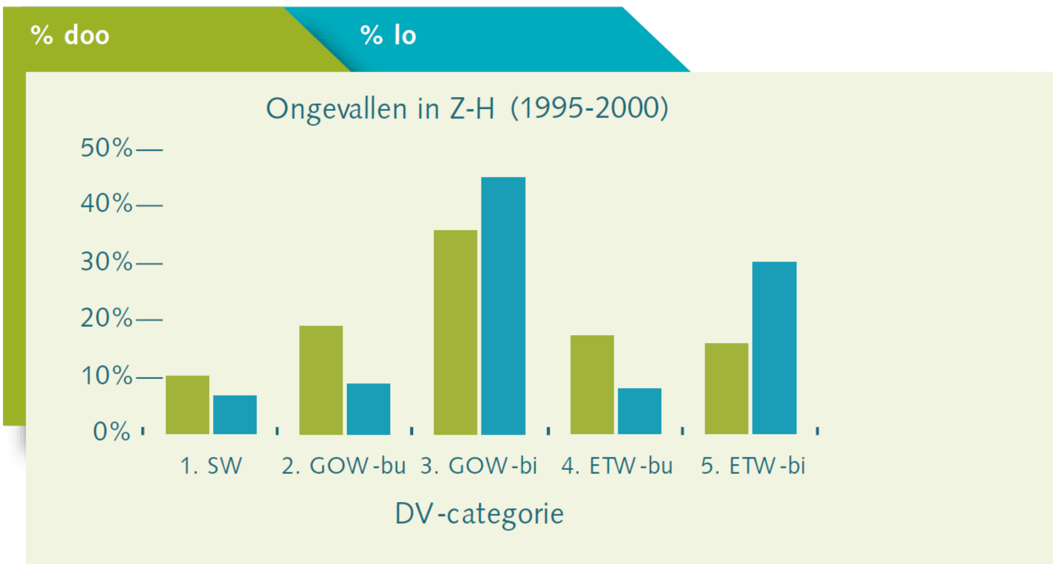


Figure 2.0.2: Share of traffic accidents regarding different road types [Dutch] (Rijkswaterstaat, 2007)

For Adaptive Cruise Control (ACC), Table 2.3 shows that there is no continue usage. Besides, the system will not be totally effective as it cannot be used in all driving situations. The results indicate that the usage in combination with the system's effectiveness are higher on highways than on regional roads (Rijkswaterstaat, 2007).

Table 2.3: Safety potential of ACC and LDW [Dutch] (Rijkswaterstaat, 2007)

Wegvak:	SW	GOW-bu	GOW-bi	Totaal/gem.
Totaal aantal ongevallen in cat.	2611	2158	6958	11727
Aandeel tot. aantal ongevallen wegvakken	12,5%	10,3%	33,2%	56,1%
Aandeel tot. aantal ongevallen	6,3%	5,2%	16,9%	28,4%
ACC	**48,80%**	**24,90%**	**18,70%**	**30,80%**
LDW	**4,70%**	**13,30%**	**11,60%**	**9,87%**
Totaal	**53,50%**	**38,20%**	**30,30%**	**40,67%**
Reductie tot. aantal ongevallen wegvakken	6,7%	3,9%	10,1%	20,7%
Reductie tot. aantal ongevallen	3,4%	2,0%	5,1%	10,5%

2.3.2 Traffic flow

The second main effect is the potential to improve traffic flow. Technologies in vehicles can sense and anticipate on lead vehicles' braking and accelerating decisions. The following vehicles can directly respond on this by smooth braking and fine speed adjustments. This leads to reductions in destabilized traffic shockwave propagation. Besides, through shorter headways, coordinated platoons, and more efficient route choices, existing lanes and intersections can be more efficiently used (Fagnant & Kockelman, 2014). For effective benefits, in-vehicle technologies, V2V and V2I techniques are essential. But as a significant part of poor traffic flow is caused by traffic incidents, crashes should decrease to improve traffic flow.

When 10% of the vehicles is equipped with Intelligent Transportation Systems, congestion could be reduced with 30%. When the penetration degree increases to 30%, it could in long term resolve most of the congestion (Nederland Innovatief Onderweg, 2010). Arem, et al. (2008) indicate that collaborating Intelligent Transportation Systems could reduce congestion with 50%. If automated driving will actually resolve most congestion, this could impose high economic benefits for businesses and consumers (Kennisinstituut voor Mobiliteitsbeleid, 2013).

Table 2.4: Effects of ACC and RCW on FOT level (Faber, et al., 2012)

		ACC and FCW	
		Cars	Trucks
Change in average travel time per trip	Motorway	0.3%	0.1%
	Rural road	-	0.02%
	Urban road	0.2%	-
Change in kilometres driven per trip[3]		0%	0%
Change in average speed	Motorway	- 0.3%	- 0.1%
	Rural road	-	- 0.02%
	Urban road	- 0.2%	-
Change in incidental delay			
Change in non-incidental delay (range, depends on road type)[4]		0% to 18%	- 26% to + 2%
Change in fuel consumption[5]	Motorway	- 2.1%	- 1.9%

'-' indicates that there is no significant effect

According to Timmer, et al. (2013), ACC can currently manage the traffic more efficient than humans is. From the euroFOT test is seems that ACC+FCW can decrease delay with 0 to 18%, depending on the road type. This is shown in Table 2.4 (Faber, et al., 2012). A simulation study of Arem, et al. (2008), shows that ACC can result in 30% less time loss in congestion.

2.3.3 Environmental savings

As a third main benefit, automated driving can reduce the energy use and emissions. It could decrease the energy use in at least three main ways: more efficient driving, lighter and more fuel-efficient vehicles and efficient infrastructure. Currently available automated systems that make driving more energy efficient are Intelligent Speed Adaption and Adaptive Cruise Control (Timmer, et al., 2013). The ability of vehicles to drive closer to each other results in savings of the system's fuel and a increase in highway capacity on existing lanes (Fagnant & Kockelman, 2014). According to KPMG & CAR (2012), platooning alone would reduce the highway fuel use by up to 20%. (Working Group Automation in Road Transport, 2013) estimates that widespread implementation of automated driving could provide fuel efficiency improvement of around 20%. Nederland Innovatief Onderweg (2010) suggests that fuel use will decrease with around 5% when ITS are used nationwide. Additionally, the need for visual input to manually navigate is reduced. Therefore, traffic lights in the streets, at intersections and highways can be less lit as the autonomous vehicle operates with means like infrared and radars. Night light is only needed for safety and security instead of for being able to driver. This also reduces the energy use (KPMG & CAR, 2012).

The CO_2 emission of a the passenger vehicles depends on the composition of the fleet and the driving behavior (Kennisinstituut voor Mobiliteitsbeleid, 2013). The smart vehicles can be manufactured lighter and more efficient, because they do not need heavy safety features anymore like reinforced steel bodies, crumple zones and airbags. A reduction of 20% of the vehicle's weight can result in a 20% increase in efficiency (KPMG & CAR, 2012). For the behavior of driving, driving speed and driving dynamics are of influence. High or low velocities cause higher emission than an in-between velocity. Also, braking and accelerating increases the CO_2 emission. The driving speed and driving dynamics highly correlate with the road type. In urban areas the speed is low and the dynamic is high, then emission will be much higher than on motorways or rural roads (Kennisinstituut voor Mobiliteitsbeleid, 2013). Emissions may decline with 10% and emission of CO2 with around 5% when several ITS systems work together (Nederland Innovatief Onderweg, 2010). Arem, et al. (2008) suggest that there may be 20% less pollution and 10% less CO_2 when Intelligent Transport Systems will work together. The CO, HC, and NOx emission reduction of an active ACC compared to a non-active ACC is 9% on highways, while the reduction on regional roads is quite higher (Rijkswaterstaat, 2007).

2.4 Future planning and challenges

Vehicle manufacturers are currently dealing with the integrity of the technology and human-machine interaction. But besides these developments that enable automated driving, public authorities are responsible for implementation planning of automated driving. The infrastructure should be integrated with the automated vehicles and the connect traffic should be coordinated and managed to gain optimal traffic flow. This will be assessed and optimized by test drives. An example is a collaboration between different public and private parties and knowledge institutions from the province of Brabant that will execute test drives in the near future. The A270 highway will be used as a real highway to further research the capabilities of automated vehicles in real driving situations (Beter Bereikbaar Zuidoost-Brabant, 2013).

Policy makers in the Netherlands have a strong focus on automated driving. To create a leader role on in the field of automated driving, Secretary Schultz van Haegen (2014), has set up a roadmap of implementation in the Netherlands. This roadmap can be seen in Figure 2.3. Between now and some years automated parking and automated congestion driving are assumed to be seen on Dutch roads. Secretary Schultz van Haegen wants to stimulated to start tests of highly automated driving between 2015 and 2020, by setting up the right legal framework. The gained experience will provide benefit and cost input to evaluate the innovation. Around 2025, highly and fully automated driving is assumed to be enabled. Litmat (2014) predicts that on a more mondial level, affordable automated vehicles are for sale between 2040 and 2050. Between 2040 and 2060 the level of the exact benefits are tangible. Finally, between 2060 and 2080 most vehicles will drive fully automated and society will highly profit from the benefits.

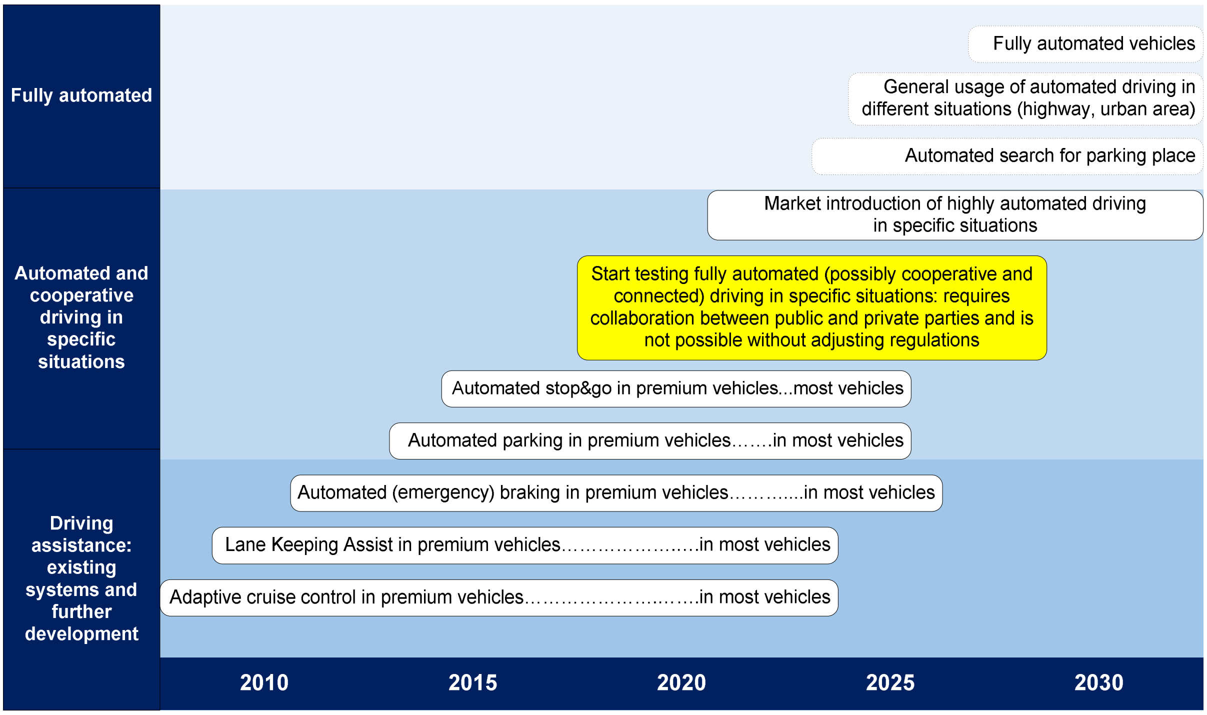


Figure 2.3: Roadmap of development of automated functions, based on roadmap of Secretary Schultz van Haegen (2014).

However, implementation of automated driving is a very unstable balance and still many issues have to be addressed (Arem, 2013; Fagnant & Kockelman, 2014; National Highway Traffic Safety Administration, 2013; SWOV, 2010b). Main issues are:

- Technical issues;
- Human-Machine Interaction for safe operation;
- Driver awareness and acceptance;
- System security / data availability;
- Liability in case of malfunctioning;
- Licensing and insurance regulation;
- Organization forms;
- Financing and business models.

2.5 Conclusions

Visions, ideas, and developments around automated driving go way back in time and after around a century of predictions, the technology is not yet matured enough to let vehicles navigate through complex environments without human monitoring. However, technical developments have enabled automated systems to take over manual control of driving tasks to a certain degree. This is enabled by systems that provide information to the vehicle, systems that communicate with each other, and systems that independently respond to situations. Currently, automated systems which are available for public can only take over control of one primary driving task or two primary collaborating driving tasks, in definite road types. However, many well-known vehicle manufacturers are testing automated systems in vehicles that aim to take over all driving tasks.

Automated driving could offer many benefits to society. The first main benefit deals with traffic safety improvement. Automated driving can prevent unsafe traffic participation, prevent unsafe actions during driving, and can reduce the impact of accidents. The second main benefit concerns an improved traffic flow. Automated driving can allow closer headways between vehicles, as the required reaction distance is much smaller than the distance needed for human reaction. Besides, communication with the vehicle's environment can result in smoother braking an finer speed adjustments. This can reduce destabilized traffic shockwave propagation. The third main benefit concerns environmental savings. A reduction of emissions and energy use is enabled by more efficient driving, lighter and more efficient vehicles and efficient infrastructure. When automated systems work together, safety can be improved by 25%, traffic flow by 50%, and pollution and CO_2 emission by respectively 20% and 10%. While currently used systems include most safety effects on highways, the eventually effects may be higher on regional roads, as the number of severe accidents is higher. Environmental savings potential is higher on regional roads than on highways, as in these circumstances the traffic flow is less fluent. However, actual effects of the systems depend on the exact actions of the system, the penetration rate and unintended side effects. Dutch Ministry of Infrastructure and Environment envisions that between 2015 and 2020, test drives can be performed on Dutch roads. They aim that around 2025, fully automated vehicles are enabled to use in all driving situations.

In the coming years, some striking challenges have to be overcome. Besides liability, costs, and privacy concerns, technical developments have to make sure that driving with automated control is more safe than driving manually. However, to utilize the safety potential of automated driving, vehicle users should be willing to release control. More insights in factors that influence this use are presented in the next chapter.

Chapter 3

Influencing the usage rate of automated driving systems

As explained in the previous chapter, automated driving is enabled by vehicle users releasing driving control. This changes interaction of the vehicle user with the vehicle and driving environment. This is further explained in 3.1, including driving circumstances that determine the interaction. When automated driving is implemented in accordance with vehicle users' preferred driving interaction, chance of a high usage rate is assumed to increase. Theory behind this assumption is explained in Section 3.2. Additionally, this section provides knowledge of how stakeholders can influence the usage rate. Furthermore, in Section 3.3 attention is paid to the choice process vehicle users go through when determining which driving situations is most preferred by them. Lastly, in Section 3.4, conclusions from this chapter are drawn.

3.1 Vehicle user, vehicle and driving environment

In a driving situation, the vehicle user and vehicle do not function on their own. It is a cohesion between the user, the vehicle, and the driving environment. This is depicted in Figure 3.1. Where the interaction user-vehicle-driving environment is the most intense, most effort should be paid to guarantee a safety and a good traffic flow (Lax, 2011). For a large extent the driving environment, together with specifics of the vehicle, determined the manual task requirements for the vehicle user (Wilschut, et al., 2012). However, automation changes the task requirements for the vehicle user. Automated driving is enabled only enabled when systems have control over the driving tasks. This changes the role of the vehicle user within the user-vehicle-driving environment interaction framework. Under high influence of trust in automation, the preferred interaction with the vehicle and driving environment is determined.

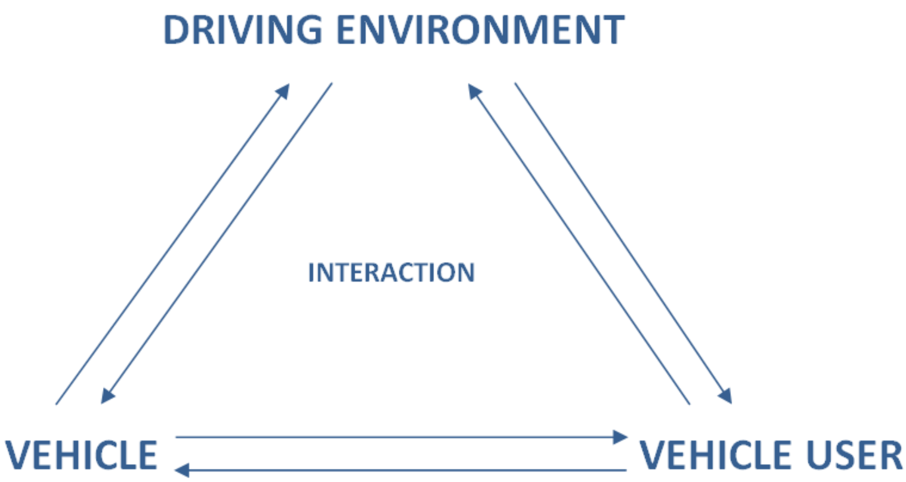


Figure 3.1: Traffic interaction framework

Lee & Moray (1994) and Vries, et al. (2003) indicate that vehicle users are biased to trust their own capabilities more than the technological capabilities when it comes to safety-critical events. When risks are involved, vehicle users do not feel at ease when technology is making decisions for them. The strong relation between trust and automated systems therefore indicates that people will only release control of when they experience sufficient trust (Lee and Moray, 1992; Muir, 1987).

The task executers (user or system, or a combination) need to navigate in the complex environment of urban streets. They pass humans only on a very limited distance. Because of this little distance between the vehicle user and other humans there is no margin of error (Lax, 2011). This suggests a reason that automation is already applied more in other transport modes. Autopilots in airplanes, automated vehicles on container terminals, automated military vehicles and automated mass-transit, are examples of modalities and environments which are (partly) automated. Although also with these modes, the impacts of an accident can be high, the immediate environment is far less complex (Weber, 2014).

Trust is seen as a continuous feedback loop. If the systems perform according to the vehicle user's expectations, trust is maintained or increased. If the expectations are not in line with the actual performance, trust is lowered (Vries, et al., 2003). This is underlined by Lee and Moray (1994) who indicate that people with positive automated systems experience will use a these repeatedly. Also Parasuraman & Riley (1997) suggest that a more and better knowledge of how automation works will increase the trust in the capabilities and may lead to usage.

The interaction between vehicle user, vehicle, and driving environment is acknowledged by previous research. Results from European Field Operational Tests (EuroFOT) show that the usefulness that vehicle users perceive with automated systems is also influenced by driving circumstances. EuroFOT has tested Adaptive Cruise Control in real driving situations. Adaptive Cruise Control (ACC) is an Intelligent Transportation System that takes over the longitudinal (accelerating and braking) driving task. These tests indicated that vehicle users found ACC most useful in normally dense traffic; primarily on highways but also on rural roads. Figure 3.2 shows also other driving circumstances in which ACC was tested. The results show that the perceived usefulness of taking over certain tasks differ per driving circumstance (Sanchez, et al., 2012).

A research by Dutch experts in the field of automated systems, van Driel and van Arem (2005), also recognize the interaction between the user, vehicle and driving environment. The results suggest that the greatest preference for assistance from the vehicle exists when driving on highways. Dutch respondents preferred the assistance less on rural roads and least of all on urban roads. It is desired from the vehicle that it provides help in critical situations, such as with imminent crashes or reduced visibility. Respondents only wanted automated control when they were maintaining a self-chosen speed on highways or rural roads, or when they were driving in dense traffic, irrespective of the road type (Driel & Arem, 2005).

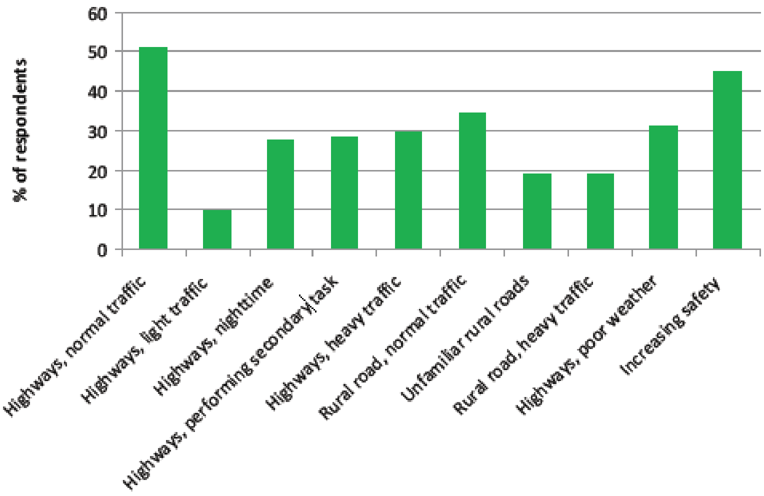


Figure 3.2: Perceived usefulness of ACC in different driving situations. (Sanchez, et al., 2012)

The following subsections will explain how vehicle users experience different driving circumstances and usage of automated driving systems. Again, here examples of ACC are used as this system takes over important primary driving tasks of humans.

3.1.1 Weather and light circumstances

Circumstances concerning weather and light highly influence the task requirements. Driving risks increase when it is dark, rainy, snowy or foggy. Because of weather circumstances, the road can be dry, wet, slushy, icy or snowy. The risk with rainy weather is even twice as high as with dry weather. Vehicle users will adjust their driving behavior to the weather, but not enough to compensate with the higher risk (Mesken, 2012). Mesken (2012) also indicates that many safety measures are already taken to reduce the risks. Examples are warnings, salt strewing and the use of winter tires.

3.1.2 Road type

Since 1997 there are national agreements on the division of road (Rijkswaterstaat & Goudappel Coffeng, 2007; SWOV, 2012b). The three different road types are: (in Dutch) stroomwegen, gebiedsontsluitingswegen en erftoegangswegen.

- Stroomwegen (highways) are aimed to have as less conflict with other motorized traffic as possible. They are characterized by physical driving way separation and non-pavement level crossings. The maximum velocity is 100-130 kilometer per hour.

- Gebiedsontsluitingswegen (regional roads) are aimed at fluent traffic flow and exchange. They are characterized by a division between fast and slow traffic and pavement level crossings. The maximum velocity is 50-80 kilometer per hour.

- Erftoegangswegen (local roads) are aimed at making plots and buildings accessible. There is no division of lanes and fast and slow traffic is mixed. The maximum velocity is 30-60 kilometer per hour.

Driving on highways is perceived as more safe and provides more comfort than local roads (Road Wiki, 2014). This is the result of the uniformity of the driving situation. Where highways contain transport modes that have nearly the same mass and speed, and where only motorized vehicles drive in one way, local roads are characterized by many mixed used transport modes. Hence, the consistency and continuity of the driving environment is an important determinant of road safety (Mesken, 2012). Therefore, the task requirement is higher for driving automated in urban areas than on regional roads or highways. This could explain results in Table 3.1. ACC is more active on highways then on regional ways, and even less on local roads: vehicle users only may trust automation in situations with low task requirement.

Table 3.1: Usage of ACC on different road types [Dutch] (Rijkswaterstaat, 2007)

	Stad	Prov.	ASW	ASW-80	Totaal
ACC uit (%)	9,1	4,2	7,8	7,4	8,0
ACC inactief (%)	86,8	73,2	49,1	49,2	66,8
ACC actief (%)	3,9	21.7	39,5	40,9	23,3
ACC actief + accel. (%)	0,2	0,8	3,6	2,5	1,9
Totaal (%)	100,0	100,0	100,0	100,0	100,0
Totaal (uren)	**503,5**	**115,9**	**590,5**	**21,8**	**1231,6**

3.1.3 Density of traffic on the road

There is a negative relation between the density and speed, comfort and safety. The higher the density on the road, the more task requirements vehicle users experience, but also the more advanced the automated system should be (Marchesini & Weijermars, 2010; Mesken, 2012). This could declare the outcomes shown in Table 3.2. ACC was relatively most used on open roads. The usage was a slightly less on more dense roads and was even less slightly used during congestion. This contradicts with results from Figure 3.2. As the results from Table 3.2 come from Dutch research and measure actual hours, these results are used as guidance.

Table 3.2: Usage of ACC for different densities [dutch] (Rijkswaterstaat, 2007)

	Vrij	Druk	Congestie	Totaal
ACC uit/inactief (%)	46,0	63,8	93,1	56,9
ACC actief (%)	49,4	33,8	6,4	39,5
ACC actief + accel. (%)	4,6	2,3	0,5	3,6
ACC actief (incl. accel) (%)	54,0	36,2	6,9	43,1
Totaal (uren)	**418,4**	**57,0**	**115,1**	**590,5**

3.1.4 Length of the trip

Vehicle users experience long distance driving different than short trips. During long distance driving people have to be concentrated for a longer time. Although navigation systems do not take over control of driving tasks, results from euroFOT show that route guidance is more often activated on long trips. This is depict in Figure 3.3 (Sanchez, et al., 2012).

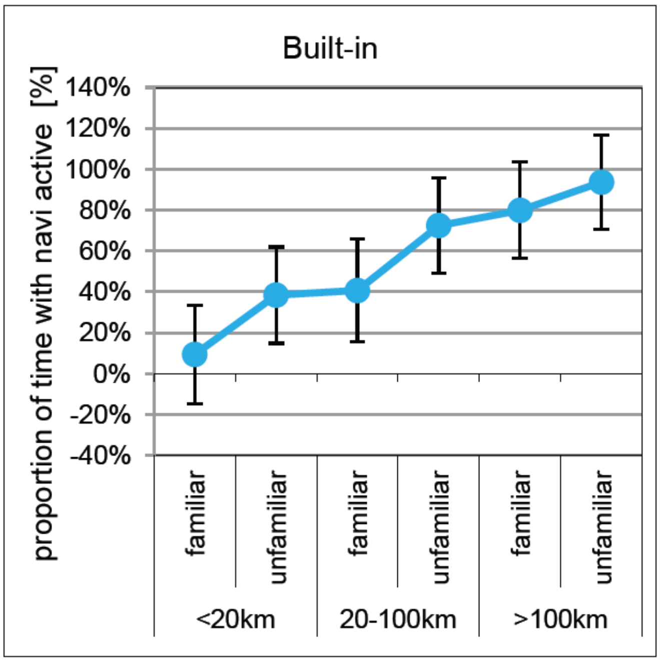


Figure 3.3: Proportion of trips with active navigation system separate from familiarity of route and length of trip (Sanchez, et al., 2012).

3.1.5 Familiarity with the route

Vehicle users seem to have more trust in themselves in familiar environments (Vries, et al., 2003). People that frequently drive the same road, tend to pay less attention to the driving environment, as the subjective experience of the difficulty level of driving decreases when the familiarity increases (Charlton & Starkey, 2011; Yanko & Spalek, 2013) Therefore, when an unforeseen traffic event occurs, risk may be higher.

3.1.6 Secondary task

Besides primary tasks, vehicle users are often also involved in other tasks during driving. Examples are talking to someone on the phone or to fellow passengers of the vehicle, or listening to the radio. Automated driving can increase the ability to perform these tasks which are mostly based on experiencing comfort or being productive while driving (Eyben, et al., 2010). Public parties have tried with several measures to lower the execution of these kind of tasks as they bring along safety risks (Govenment of the Netherlands, n.d.). In Section 2.2.1, these comfort related tasks were addressed as tertiary tasks. But to make the term and meaning more comprehensible, in the latter of the thesis this will be referred to as secondary task.

3.2 Implementing automated driving in line with users' preferences

The previous section has indicated attributes that could influence the willingness of vehicle users to release control. The willingness to release control is a requirement for vehicle users to use automated systems. KPMG & CAR (2012), KMPG (2013) and Litman (2014) explain that the achievement of potential benefit levels is depended of whether or not a critical user mass will use automated systems. Hence, In order to benefit from the earlier mentioned effects of automated driving, automated driving should spread among vehicle users. An example of how automated vehicles could spread is presented in Figure 3.4. This is referred to as the diffusion process, as further explained in the next subsection. Stakeholders that have influence on this process are described in Subsection 3.2.2.

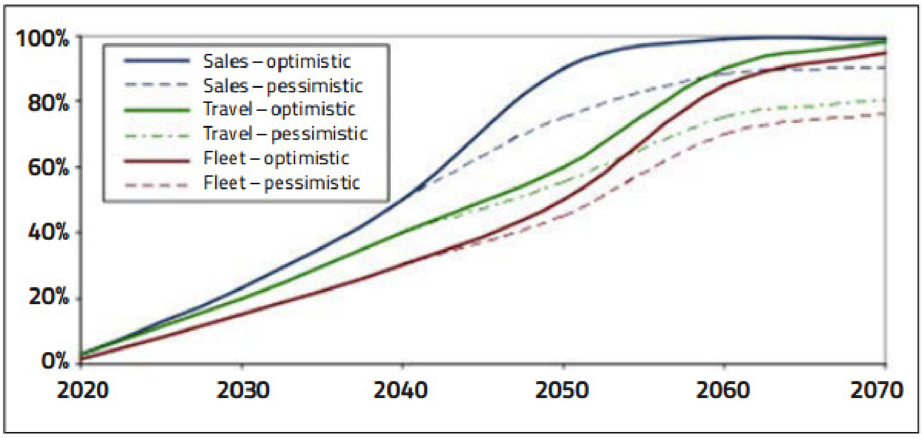


Figure 3.4: Deployment rates of projected automated vehicle sales, fleet and travel (Litman, 2014)

3.2.1 Diffusion process

Rogers (2003) proposed the Diffusion of Innovations theory to describe a diffusion process of innovations. It focuses on the market share that grows when successive groups that adopt an innovation, as depicted in Figure 3.5 by the yellow line. Although this theory concerns and individuals' decision whether not to adopt a technological innovation, while this thesis concerns willingness to release control to a technological innovation, it is assumed that the spread among users follows the same diffusion path. Therefore, this theory is used to describe how automated driving may spread among vehicle users. The faster vehicle users start to automated driving, the more society could benefit from the technology.

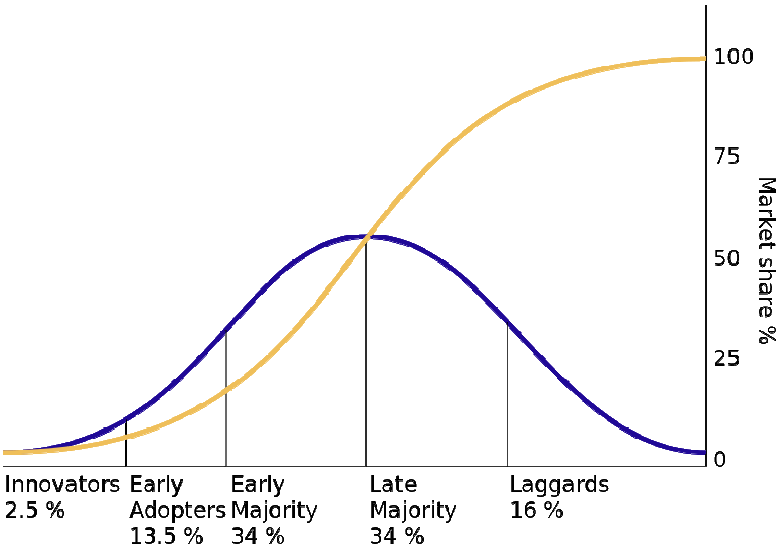


Figure 3.5: General diffusion process as proposed by Rogers (2003)

Diffusion is defined by (Rogers, 2003) as "Diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system". In a sequence of steps, from niche to widespread level, the diffusion occurs. Niches provide learning opportunities for different dimensions, such as technology, user preferences, regulations and infrastructure. When the niche accumulates, more stakeholders will support the innovation. When stakeholders come together, the system becomes increasingly stable (Rogers, 2003). Therefore, niches are important. At a point in time, the critical mass ensures self-sustaining use. The replacement of human driving to automated driving is assumed to happen in gradual fashion, as creation of a new system takes place. This is depict in Figure 3.6.

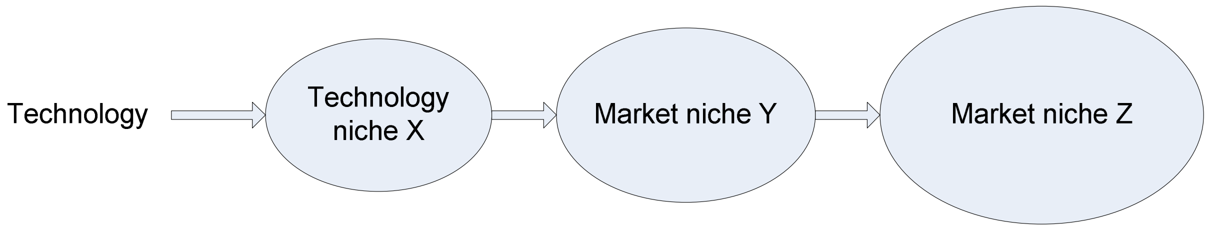


Figure 3.6: Spread of technology among niches

The uptake by vehicle users can be divided in five categories: innovators, early adopters, early majority, late majority and laggards, which are depict under the blue line in Figure 3.5. Innovators are characterized by their willingness to take risks, they have a high social status and financial wealth. They have close contact to scientific sources and interact with other innovators. Early users have the highest degree of opinion leadership. They have a higher social status, financial liquidity, advanced education and are socially forward. In addition, early users are more discreet in adoption choices than innovators. The early majority has an above average social status, contact with early adopters. Late majority only adopts an innovation after the average participant has done this. They are typically more skeptical about an innovation and have little financial liquidity. Laggards are the last group to adopt an innovation. They show little to no opinion leadership and an aversion to change-agents. They focus on traditions and have the lowest social status and financial liquidity.

Litman (2014) expects that the implementation rates are higher in areas that are more affluent (residents can more quickly afford automated vehicles), more congested (potential benefits are greater) and have more public support. J.D. Power and Associates 2012 U.S. Emerging Technologies Study (2012) and KPMG (2013) also have given an indication that not all people are even likely to embrace automated driving. However, their results do not correspond. A reason for these differences could be the research approach. While Power and Associates have done a research involving 17.400 vehicle owners, KPMG's results come from a focus group of 32 participants. Power and Associates have found that males prefer fully automated driving more than females. Moreover, younger people are more willing to purchase an automated vehicle than older generations. KPMG has found that females are little more willing to ride in automated vehicles than males. Additionally, older people are more willing than younger people. The results concerning vehicle ownership are the same for both studies: premium vehicle owners are more interested in automation than mass market vehicle owners.

This section has indicated that a critical user mass should use automated systems to achieve the potential benefits for safety, traffic flow and environmental savings. To enable widespread use, the first focus should be on a niche user group that is expected to be the first to use this systems. According to Rogers (2003), these may be vehicle users with high social status, financial liquidity and advanced education. Furthermore, literature indicates that there could be a difference in gender and age concerning the willingness to embrace automated driving. The next sections pays attention to stakeholders which have power to influence the use by transport and market implementation planning.

3.2.2 Stakeholders

Different stakeholders have power over transportation and market planning concerning automated driving. and therefore they can influence on vehicle users. The following stakeholders will be identified: public parties, consumer supporting organizations, vehicle manufacturers, and vehicle users. They all have their own interests, problem perceptions, values, preferences, strategies and resources (Geels, 2005).

Public parties

The public parties can use its power by road infrastructure, education, public campaigns, regulations and enforcement, rewarding, knowledge development and collaboration with private parties (Ministry of Transport, Public Works and Water Management, 2009; Timmer, et al., 2013). Current measures to promote a certain mobility behavior are the tax people pay for ownership and use of vehicles, such as motor vehicle tax (Dutch: motorrijtuigenbelasting), tax on passenger vehicles and motor cycles (Dutch: belasting van personenauto's en moterrijwielen), and excise on fuel (Ministry of Transport, Public Works and Water Management, 2005). Below, public parties are split up in policy makers, regulators and transportation planners.

Policy makers - The Netherlands has a one of the lowest or the lowest number of traffic deaths in world level. The central aim of policy makers is to lower this number to be able prevent and limit grief and societal costs. This is a big challenge as mobility grows and society is ageing. Therefore, innovation concerning mobility is very relevant for society. Besides the safety aspect, policy makers adjust policies in the field of traffic flow and environmental savings, as they can make mobility more efficient and cleaner. When making decisions concerning the mobility innovations, policy makers will take in account side effects, public support and the costs and benefits (Kennisinstituut voor Mobiliteitsbeleid, 2013).

Regulators - Practice has thought that innovative products are usually applied on voluntary bases. When the support is growing, the application becomes standard or it will be legally obliged (Ministry of Transport, Public Works and Water Management, 2009). However, liability is a crucial factor for user acceptance. To increase public support, regulators can take measures on the basis of behavior, vehicles and infrastructure. These measures have influence on societal interest, effectiveness, proportionality, and costs.

Transportation planners - One of the important considerations for transportation planners is how to mix automated vehicles with non-automated vehicles (Fagnant & Kockelman, 2014). Partial automation is already available within mixed traffic. Zwanenveld and Arem (1997) see solution introducing an automated driving lane. When the adoption rate is low, the road capacity will increase. However, a high adoption rate, including automated infrastructure can lead to high capacity improvements. An important issue here is the connection of high capacity automated driving lanes with local roads. This connection is required for receiving and dispersing traffic onto and off the automated driving lane.

Consumer supporting organizations

Consumer supporting organizations like ANWB or Veilig Verkeer Nederland support vehicle users to increase their driving benefits. They gain insights in what developments are possible to benefit from, but also gain insights in what developments are preferred by the driver. These groups will perform tests with vehicle applications in the real world. With this, it will be questioned how automated driving can be in line with users needs (ANWB, 2014; Veilig Verkeer Nederland, 2014).

Vehicle manufacturers

Vehicle manufacturers have several aims, whereof the main aim mostly is gaining high market share. Reaching this aim is done by different strategies. Vehicle manufacturers want to connect with the needs of its consumers, by increasing consumers' benefits, ease and comfort. Secondly, they want to distinguish themselves and create a strong profile. Thirdly, they attempt to lower the costs and to raise the revenues (Ministry of Transport, Public Works and Water Management, 2009).

The vehicle manufacturers distinguish themselves by developing products that lead to better safety and comfort for the users. A vehicle manufacturer could get high market share when it appropriately implements these techniques in vehicles which deliver a driving experience that is esthetically and emotionally pleasing to the users. The vehicle manufacturers should offer an attractive value proposition which is customized for different user groups in the market. This will increase the willingness to pay (KPMG, 2013).

Vehicle users

Vehicle users are stakeholders who eventually determine in which level automated driving will benefit society. They are the ones who make the decision to use or not use a certain level of automation in a certain driving situation. As indicated in Chapter 1, an critical motive for this decision is the control they want to have when driving automated. Likewise, there are more motives that influence the use of a certain level of automation in a certain driving situation. Main motives which can be split up in instrumental and affective motives. Motives that are often mentioned in literature can be seen in Table 3.3 (e.g. Anable & Gatersleben, 2005; Beirão & Cabral, 2007; Boer & Hoedemaeker, 1998; Gardner & Abraham, 2007; Hagman, 2003; Jensen, 1999; Steg, et al., 2001). As stated in the scope of this research, these factors will not be further researched.

Table 3.3: Instrumental and affective driving motives

Instrumental motives	Affective motives
- Speed;	Comfort;
- Safety;	Control;
- Financial costs;	Excitement and sensation;
- Energy use;	Perceived stress;
- Physical effort or exertion;	Relaxation;
- Travel time;	Privacy.
- Convenience;	
- Predictability.	

3.3 Choice process

In previous sections of this chapter, it is explained that the role of the vehicle user will change when he or she will release driving control. The changed role of the vehicle user within the traffic interaction framework could change user's preferences concerning its interaction with the vehicle and the driving environment. Driving circumstances are presented that determine the experience of interaction. Stakeholders can influence these determinants. By having insights in the preferred driving circumstances and the level of automation, stakeholders can adjust their transport and market plans to the preferences of vehicle users.

Insights in which choice vehicle users would make in a certain driving situations, can be obtained by a discrete choice modeling. A discrete choice model can describe the decision process of vehicle users in a particular context. Within discrete choice modeling, alternatives and attributes are used. Attributes represent the level of automation and the driving circumstance. The driving situation that is formed by these attributes are referred to as alternatives. To model the vehicle users' decision process, individuals are asked to make trade-offs among different attributes within an alternative. The advantage of a choice-approach is, that compared to more traditional approaches, individuals will less overestimate the importance of unimportant attributes, as well as underestimate the importance of important attributes (Marchau, et al., 2001).

A general individual choice process is described by Louviere, et al. (2000), and is depicted in Figure 3.7. First, the vehicle user becomes aware of its needs. This is followed by learning about technology and circumstances which can satisfy these needs. Vehicle users will evaluate which alternatives are available to attain their objectives. With this information, the vehicle users will form a utility function which involves valuing and trading off attributes that have influence on their decision. Depending on other constraints, they decide which alternative they want to choose.

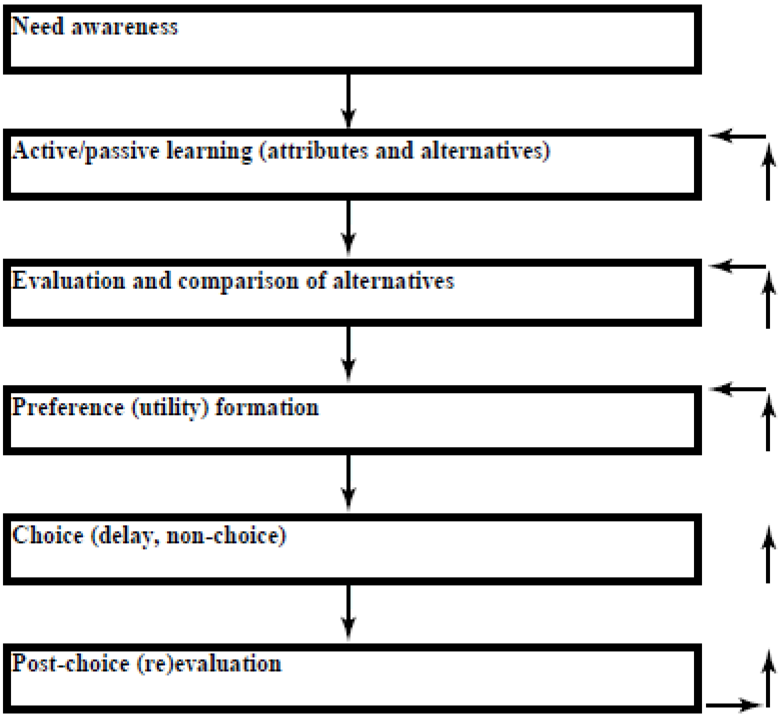


Figure 3.7: Overview of the consumer's choice process (Louviere, et al., 2000)

3.4 Conclusions

Automated driving results in a new role for the vehicle user. The interaction between vehicle, vehicle user and the driving environment has changed, as control of driving tasks is released to automated systems. This could change the users' perception of driving and their driving preferences. These preferences are highly influenced by the trust vehicle users have in automation. Several driving circumstances are described which could influence vehicle users' willingness to use automated systems. These are, weather and light circumstances, road type, length of the trip, density of traffic on the road, familiarity with the route and whether or not to perform a secondary task. Vehicle users' willingness to release control is a precondition to gain potential societal benefits. Literature explains that only when a critical mass uses automated systems, society will achieve benefits from the technology. The spreading of this use can be characterized by a diffusion of automated driving among a certain group, as proposed by Rogers' Diffusion of Innovations theory. The relative speed at which a vehicle user will use automated systems is related with the user's background. Vehicle users with higher social status, financial liquidity, more advanced education and are assumed to use automated systems more early than vehicle users with lower social status, less financial liquidity and lower education. Thus, it is important to appeal transportation and market implementation plans to the right user groups in order to gain a high usage rate. Main stakeholders that could influence transportation and market implementation plans are policy makers, regulators, transportation planners, societal interest groups, vehicle manufacturers, and vehicle users. The vehicle users are the one eventually choosing to release control in a particular driving situation. The choice process that vehicle users experience in different driving situations, can be described by discrete choice models, which are explained in the next chapter.

Chapter 4

Measuring discrete choices

In the previous chapter, the interaction between vehicle user, vehicle and driving environment of automated driving is outlined. A combination of different driving circumstances form a specific driving situation. In this chapter provides theory about the weights that potential users place on certain automated driving situations. This weight is named 'utility'. Utility (U_i) tells something about how much a driving situation, or in a more general term 'alternative', is preferred (Hensher, et al., 2005). This chapter starts with a more detailed explanation of maximum utility. This is followed up by defining three types of models that predict choice. Respectively Multinomial logit model in Section 4.2; Latent class model in Section 4.3; and Mixed logit model in Section 4.4. In Section 4.5, it is described how the predicated power of the models can be calculated. The last section will contain conclusions from this chapter.

4.1 Utility maximization

According to the random utility theory, it is assumed that an individual *n* will base the preferred choice amongst *i* alternatives with attributes *j* within a choice situation on the alternative with the highest utility. The individual respondent chooses for alternative *i* if and only if U_i > U_i ∀ *j* ≠ *i*. (Train, 2009). The individual will evaluate the set of alternatives rationally. The utility associated with each alternative within a choice situation is represented by a utility function (Hensher & Greene, 2002).

$U_i = V_i + \varepsilon_i$ (1)

Where
V_i is the indicated structural utility associated with alternative *i.* This component can be measured as it is related to the alternatives in the choice situation;
ε_i is the error term, which cannot be observed by the researcher but are known to the individual respondents.

With
$V_i = \beta_0 + \Sigma_j \beta_{jk} * X_{ijk}$ (2)

Where
β_0 is the constant term, indicating on average the role of all unobserved sources of utility;
β_{jk} is the parameter associated with attribute *j* and level *k*;
X_{ijk} is the effect coded attribute-level *k* of attribute *j* of alternative *i*.

With
$\beta_{jk} * X_{ijk} = v_{ijk}$ (3)

Where
v_{ijk} is the part-worth utility associated with alternative *i*, with attribute *j*, with regard to level *k*.

The constant term β_0 is equal to the mean of the observed alternative ratings. β_0 indicates the general attitude towards a certain alternative. The attitude can be positive or negative. The bigger the value of β_0 parameter, the more influence it has on the overall preference. The part-worth utilities are expressed in terms of the deviation from this mean. The sum of an attribute's part-worth utilities is equal to zero (Marchau, et al., 2001)
.
To get insights in the probability that a certain driving situation is chosen above another driving situation, utility will be derived from models that estimate choice behavior. There are several options to model choice behavior. The aim is to choose for a model that best represents the underlying choice process that generates the observed data. In the following sections, three models that can give insights in preferences of different target groups are discussed.

4.2 Multinominal logit model

Multinomial logit (MNL) model is the most basic and widely used model for analyzing discrete choice modeling. It has a short estimation time and its computation is simple. Also the goodness of model's fit is easy to measure. MNL model gives one set of globally optimal parameters and therefore the parameters are easy to interpret. The model is homogeneous of degree zero in attributes. MNL model has an important and strong assumption, namely that the unobserved error term is independently and identically distributed (Louviere, et al., 2000). Another main assumption is that the ratio of probabilities of choosing between alternatives is independent of the choice set. With the MNL model, the probability that a certain alternative has the highest utility can be predicted by the following formula (Hensher, et al., 2005):

$$P_i = \frac{e^{V_i}}{\Sigma_i \, e^{V_i}} \qquad (4)$$

Where
P_i is the probability that alternative *i* is chosen.

4.3 Latent class model

Latent class (LC) model has an improved model fit over the Mutlinomial logit model. Also the parameters of the Latent class (LC) model are also easy to interpret. With Latent class model, this heterogeneity is observed by discrete parameter variation. In a an MNL model these factors are not directly observed. Respondents who have similar observed variable distributions are implicitly grouped into the same latent class with parameters to be estimated. A drawback is that with this model, it will not be known by the researcher which particular individual contains which class (Greene & Hensher, 2003). Another disadvantage of the LC model is that an extra analysis needs to be done to decide the number of classes.

With the parameters given by the LC model, the probability that an individual with a certain characteristic belongs to a certain class can be calculated. This is expressed by the following formula (Heijden, et al., 1996; Greene & Hensher, 2003):

$$P_n(class = c) = H_{c|n} = \frac{e^{\lambda_c z_n}}{\sum_{c=1}^{C} e^{\lambda_c z_n}} \qquad (5)$$

Where
$H_{c|n}$ is the probability of an individual *n* belonging to class *c*;
λ_c is the vector of utility weights belonging to characteristics *z* specified for class *c*;
z_n is the vector of observed individual, situation invariant, characteristics of individual *n*.

Individual specific class probabilities are calculated with the following formula (Kikulwe, et al., 2009; Greene & Hensher, 2003):

$$P_{c|i} = \frac{P_{i|c} * H_{c|n}}{\sum_{c=1}^{C} P_{i|c} * H_{c|n}} \qquad (6)$$

$P_{c|i}$ is the probability of individual *n* with a certain probability of belonging to class *c,* chooses alternative *i*;
$P_{i|c}$ is the probability of choosing alternative *i*, given the class *c* (same calculation as with MNL probability).

4.4 Mixed logit model

Mixed logit (ML) model is a more adequate model than the Latent class model n terms of its overall flexibility and range of behavior it can accommodate. The Mixed logit model can explain individual differences in the mean of the attribute levels (Greene & Hensher, 2003). It differs with MNL as Mixed logit does also not require to make specific assumptions about the distribution of parameters across individuals. The disadvantage is that analyzing this decomposition is not easy. Estimating the parameters is time consuming and parameters are difficult to interpret.

A distribution to the random component within the utility function can be assigned to gain more insights in the individual choice process. The mean and standard deviation of one or more random parameters can be decomposed to reveal sources of systematic taste heterogeneity (Greene & Hensher, 2003).

With an ML model heterogeneity can be modeled, estimating the range of each utility weight among the sample. It can be seen if utility weights are approximately equal for the whole sample or severely differ. The utility function associated with alternative *i* as evaluated by each individual *n* is represented by the following formula:

$$U_{ni} = \beta_n * X_{ni} + \varepsilon_{ni} \qquad (7)$$

For the Mixed logit model the β's are the not fixed for the total sample but are different for each respondent. β_n is not observed by the researcher and is treated as a stochastic influence, determined by, where θ are the parameters of the distribution of β_n over the sample, such as the mean and the standard deviation of β_n (Hensher & Greene, 2002; Train, 2009). For a given value of β_n the conditional choice probability that individual *n* chooses alternative *i* is:

$$L_{ni}(\beta_n) = \frac{e^{\beta_n * X_{ni}}}{\Sigma_i\, e^{\beta_n * X_{ni}}} \qquad (8)$$

As β_n is not given, the (unconditional) choice probability is equation 12 integrated over the density of β_n. This equation is shown below (Hensher & Greene, 2002).

$$P_{ni} = \int L_{ni}(\beta)\, f(\beta \mid \theta) \mathrm{d}\beta \qquad (9)$$

Where
$L_i(\beta)$ is the likelihood of an individual's choice if they had this specific β;
$f(\beta \mid \theta)$ is the density of β where θ are the fixed parameters of the distribution;
P_{ni} is the probability of individual *n* chooses alternative *i*.

The probability cannot be exactly calculated as the integral does not have a closed form. So to approximately estimate the parameters β's of the Mixed logit model, simulation is applied. These parameters are (in this thesis) normally distributed with θ referring collectively to the mean and standard deviation parameters. For any random value within the normal distribution, β can be calculated by inversing the normal cumulative distribution for the specified mean and standard deviation. With this β, the logit probability L_{ni} is calculated. The choice probability P_{ni} is then calculated by repeating this step and averaging the results as in equation 10 (Train, 2009).

$$SP_{ni} = \frac{1}{R} \sum L_{ni}(\beta) \qquad (10)$$

Where
SP_{ni} is the simulated probability that an individual *n* chooses alternative *i*;
R is the number of draws of β.

4.5 Model's goodness-of-fit

To get insight in whether the models predict the observed data well, the model's fit will be calculated. It can be tested if the estimated parameters of the model provide an improvement of the model without estimations. Also, different models with both estimated parameters can be compared to know which one has the best predictive power. In this research, maximum Pseudo R^2, likelihood ratio test and to information criteria are applied.

The basis of the fitness or comparison tests, is the maximum likelihood estimation. This is based on a set of parameters that produce the observed sample most often (Train, 2009). The maximized log likelihood function can be defined by the following formula:

$$LL_M = \sum_{n=1}^{N} \sum_i f_{ni} \left(P_{ni}\right) \qquad (11)$$

Where
LL_M is the log likelihood function for the estimated model, maximized with respect to estimated parameters;
N is the sample size;
f_{ni} is the choice of individual *n* for alternative *i*, which is equal to 1 if *i* is chosen and 0 otherwise;
P_{ni} is the probability of individual *n* chooses alternative *i*.

4.5.1 Pseudo R²

The Pseudo R^2 measures how the estimated model performs against a model where all parameters are set to zero. Louviere, et al. (2000) indicate that a model's Pseudo R^2 should be between 0.2 and 0.4. Models with R^2 value below 0,1 are considered as weak. According to Hensher, et al. (2005) 0,3 represents a decent model fit.

$$R^2 = 1 - \frac{LL_M}{LL_0} \qquad (12)$$

Where
LL_M is the log likelihood function for the estimated model;
LL_0 is the log likelihood function for the model estimated with no parameters;
R^2 suggests the level of improvement between the two models and falls between 0 and 1.

When the number of parameters increases, the adjusted psuedo R^2 should be examined. When the value of this estimation increases with parameters raising, it indicates the existence of heterogeneity in the data.

$$\text{adjusted } R^2 = 1 - \frac{LL_M - p}{LL_0} \qquad (13)$$

Where
p is the number of parameters.

4.5.2 Likelihood ratio

The likelihood ratio test is another popular form of testing the model fit. It is based on the likelihood function and therefore has the same foundation as the psuedo R^2. The likelihood ratio is the likelihood of the estimated model divided by the likelihood of the base model with zero parameters. The likelihood ratio-test expresses how much more likely the data under one model is than under the other model. This ratio is between 0 and 1 and the less likely the assumption is, the smaller the ratio will be. The likelihood ratio can be compared to a critical value to decide if the estimated model outperforms the base comparison model. The formula for the likelihood ratio is described as:

$$D = -2\,(LL_0 - LL_M) \qquad (14)$$

Where
D is the likelihood ratio of two models.

It should be compared to a chi-square statistic with degrees of freedom equal to the difference in number of parameters between the compared models. If D is larger than the chi-square the ratio the assumption is rejected, and the estimated model is preferred over the model with restrictions. If D is less than the chi-square, it cannot be concluded that the estimated model is better than the base model (Hensher, et al., 2005).

For the Latent class model and the Mixed logit model, not all terms of the smaller model occur in a larger model. Therefore, a likelihood ratio test will only be applicable for the Multinomial logit model (Greene & Hensher, 2003).

4.5.3 Information Criteria

Information criteria are applied when an estimated model should be compared with another estimated model. Akaike information criterion (AIC) and Bayesian Information Criterion (BIC) are suggested as good indicators (Akaike, 1974; Schwarz, 1978). The lower the value, the best the model represents the data (Kass & Raftery, 1995).

AIC is defined by: $$\text{AIC} = -2 * LL_M + 2 * p \quad (15)$$

BIC is defined by : $$\text{BIC} = -2 * LL_M + \ln(N) * p \quad (16)$$

Where
N is the number of observations.

4.6 Conclusions

In this chapter theory is presented of how to estimate choice behavior of vehicle users. Three models that are introduced are Multinomial logit model, Latent class model and Mixed logit model. All three models have their advantages and disadvantages. While a Multinomial logit model is relatively simple, it does not take into account heterogeneity between individuals or groups of individuals. With a Latent class model heterogeneity can be estimated by allowing different preferences between discrete classes. Mixed logit models are even more flexible as they allow to estimate individual taste heterogeneity. However, Mixed logit models are not so easy to analyze. As chapter 3 indicates, it is valuable to get insights in customized preferences within different user groups. Therefore, analyzing a Latent class model and Mixed logit model is most interesting. How well these models predict the actuality, depends on the goodness of fit which could be calculated on the basis of the maximum likelihood estimation, a set of parameters that produces the observed sample most often. The data-input for the models comes from a discrete choice experiment, which will be elaborated in the next chapter.

Chapter 5

Experiment design

A discrete choice experiment will be set up to predict discrete choices of vehicle users with regard to automated driving situations. This chapter will pay attention to how this experiment is constructed. For a proper design, the guidelines of Hensher, et al. (2005) are applied. In Section 5.1 the problem statement of this research is refined. Secondly, with insights from literature, attributes and attribute-levels are identified and refined. In Section 5.3, the experimental design is considered. Next, in Section 5.4 the experimental design is generated and attributes are allocated. This is followed in Section 5.5 by setting up proper choice sets. The construction of the experiment is finished, as explained in Section 5.6. This chapter concludes in Section 5.7 with an overview the constructed experiment.

5.1 Research question refinement

As discussed in previous chapters, one possibility to increase traffic safety, improve traffic flow and achieve significant environmental savings is automated driving by releasing driving tasks to automated systems. The more vehicle users are willing to release control in different driving situations, the more benefits for society can be obtained. However, literature indicates that it is not granted that vehicle users are willing to release control. Vehicle users seem to have more trust in their own task capabilities than in task capabilities of the technology. Certainly when the driving situation is more complex, they tend to be unwilling to release control. The willingness to ride with automated systems seems to differ per user group.

Therefore the main research question is:
Which level of automation and which driving circumstances contribute to the willingness of different vehicle user groups to release driving control?

5.2 Identification and refinement of attributes and attribute-levels

The attributes that influence the choice behavior of interest form an alternative. Together, these alternatives form choice sets. The choice sets have a fixed number of alternatives. The assignment of the respondents is to indicate which alternative he or she is most likely to choose (Hensher, et al., 2005).

According to Hensher, et al. (2005), the second step involves selecting alternatives and attributes. In this experiment only labeled alternatives are defined. Firstly, because the unlabeled alternatives are assumed to be less correlated with the attributes than labeled alternatives, they may be more robust in terms of violating the assumption that error terms are independent and identically distributed. Secondly, while labeled alternatives may take effects into account which respondents may have learned to associated with different driving situations, this does not occur with unlabeled alternatives. Thirdly, using labels results in many alternatives, while not using labels results in limited alternatives (Hensher, et al., 2005).

As the second step involved the determination of a list of attributes and attribute-levels, insights of literature from is used. One of the identified attributes is the level of automation. The levels that are associated with this attribute are presented in Sub-section 2.2.2. The explanation of the role of the driver and system per level are quite understandable. However, it is assumed that the labels associated with the levels are not so easy to interpret for vehicle users that are participating in this experiment. The level of automation is directly linked with level driving tasks that has to be released. Therefore, the experiment and analysis of the data, the attribute 'level of automation' is replaced by 'level of released driving tasks', including associated levels. In the conclusion again 'level of automation' is used in order to clearly answer the main question.

Other attributes come from Section 3.1. Weather and the level of light seem to have influence on the task environment. However, these attributes are very hard for respondents to trade off, which can influence the predictive power of the results. Moreover, they have little to no influence policies or action for public parties, consumer supporting organizations and private parties. Therefore, they are not taken in account in this research. The remaining six attributes, including the associated levels used in the experiment, are presented in
Table 5.1.

Table 5.1: Selected attributes and corresponding levels

Attribute	Level	Label
Level of released driving tasks	0	Release very little tasks
	1	Release little tasks
	2	Release many tasks
	3	Release all tasks
Road type	0	Highway
	1	Regional road
	2	Local road
Length of trip	0	<20 km
	1	20-100 km
	2	>100 km
Density on road	0	Low
	1	Average
	2	High
Familiarity with route	0	Familiar
	1	Unfamiliar
Secondary task	0	Yes
	1	No

5.3 Experimental design considerations

The primary source of choice response used in this research is stated choice data. Stated choice data derives choices that are made or stated given hypothetical situations. On the contrary, revealed preference/choice data derives actual choices of decision makers in a real market (Hensher, et al., 2005). With stated choice approach method, reliable estimates of the relative importance of each of the attributes are provided. It allows robust understanding of how individuals make choices by observing multiple choices from one individual. Individuals can be assigned by corresponding user groups. This enables the models to examine the choices made by different user groups (Dumont & Falzarano, 2012). The task is to make the hypothetical scenarios as realistic as possible. A drawback of applying stated choice is that it uncertain how much faith can be put in the results as it is unclear of individuals are actually doing what they stated they would do when the case arises. Moreover, stated choice is only reliable when respondents understand, are committed and can respond to tasks (Ortuzar & Willumsen, 2011).

5.4 Generation of experimental design and allocation of attributes

The next step is to combine levels into alternatives which can be evaluated by the respondents. They are explicitly forced to make trade-offs among attributes in the alternatives (Marchau, et al., 2001). A full-factorial design would result in 432 alternatives ($4^1 * 3^3 * 2^2$). This is based on an unlabeled experiment where the number of alternatives is calculated by L^A. *L* represents is the number of levels and *A* the number of attributes. As it is impossible to let respondents adequately evaluate this number of alternatives, the number of alternatives evaluated should be reduced. This can be done by making assumptions on how decision-makers combine part-worth utilities into structural utilities. This results in a fractional factorial design which consists of 16 alternatives. These are based on a scheme designed by Addelman (1962) which estimates the main-effects of the different attributes. This reduction results in the fact that this research does not involve interaction effects between attributes. This means that the structural utility is assumed equal to the sum of separate part-worth utilities (Louviere, 1988). In Table 5.2 a matrix shows 16 rows which represent the alternatives and 6 columns which represent the attributes.

Table 5.2: Experiment alternatives

Treatment combination	**Level of released driving tasks**	**Road type**	**Length of trip**	**Density on road**	**Familiarity with route**	**Secondary task**
1	0	0	0	0	0	0
2	0	1	1	2	1	0
3	0	2	2	1	1	1
4	0	1	1	1	0	1
5	1	0	1	1	1	1
6	1	1	0	1	0	1
7	1	2	1	2	0	0
8	1	1	2	0	1	0
9	2	0	2	2	0	1
10	2	1	1	0	1	1
11	2	2	0	1	1	0
12	2	1	1	1	0	0
13	3	0	1	1	1	0
14	3	1	2	1	0	0
15	3	2	1	0	0	1
16	3	1	0	2	1	1

5.5 Generation of choice sets

The alternatives are randomly paired in combinations of two. This results in eight choice sets, presented in Table 5.3.

Table 5.3: Generated choice sets

Choice set	Driving situation 1	Driving situation 2
1	4	9
2	11	13
3	3	6
4	14	15
5	2	16
6	1	10
7	5	7
8	8	12

Figure 5.1 illustrates an example of a choice set. As can be seen, the title of the first alternative does not convey any information to the decision maker, other than that it is the first of the two driving situations. This is the same for the second alternative. As this is a stated choice experiment, the decision maker should make a choice between at least two alternatives, given the level each alternative assumes. A constant base 'geen van beide' is added to the choice sets. This can be chosen by respondents who are not willing to choose for one of the first two alternatives.

Figure 5.1: Example of a choice set [Dutch]

5.6 Survey instrument

A Dutch internet-based questionnaire is distributed to a random sample of respondents in the Netherlands. The questionnaire is presented in Appendix III. This questionnaire is set up in the Berg Enquete System, an online survey tool.

The respondents are shortly informed about the objectives and procedure of the survey. As the concept of automated driving is not well-known, respondents are smoothly introduced with this. It is aimed to construct the survey with appropriate questions and information which are established in a way that they are understandable for the respondents. Moreover, questions and information should relate to the respondent's current level of experience and appear realistic (Ortuzar & Willumsen, 2011). Besides, there should not be ambiguity, include different vernacular and it should not contain biased questions (Hensher, et al., 2005). The questionnaire is tested against these sorts of flaws by around 10 test respondents. A second bigger test-questionnaire involves 50 respondents.

There are two sources which influence the choice behavior. Firstly, attributes relate to the description of the alternative. Secondly, characteristics that relate to the individual's prejudice which is represented by its socio-economic variables and its context influence (Hensher, et al., 2005). To get insights in both sources of influence, the questionnaire consists, besides a stated choice part, of individual's background questions. The aim is to find homogeneity within groups and heterogeneity between groups. With this information, different groups can be addressed more appropriately. Consumer characterization can be done by socio-demographic factors, perceptions, attitudes and habits (Beirão & Cabral, 2007). In the light of automated driving, therefore insight is provided by questioning the participant's driving experience, its view on ITS and basic socio-demographic and psychographic variables. In the following four sections these three parts, including the stated choice part, are explained. However, before questioning respondents about personal related factors, they have to oblige to one requirement: having a passage vehicle driver's license (in the Netherlands: driver's license B). This decision is made as one can only make a proper choice between alternatives if they have experience with driving.

5.6.1 Part 1: Driving experience and personality traits regarding driving

First, a set characterizations is presented by questioning respondents about their driving experience, kilometers driven per year, and whether or not they owned a vehicle. Also, it was asked if they agreed with the following sentence: I consciously use fuel to save the environment. The characterization is shown in Table 5.4. The link of the characterizations with automated driving is not yet made by literature. However, these points all link to driving and questioning this, can give insights if there is a link.

Table 5.4: Driving experience factors

Driving experience	**Average kilometers per year**	**Most driven vehicle**	**Environmental aware driving**
Less than 5 year	Less than 10.000	Own vehicle	Very much disagree
5-19 year	10.000-30.000	Lease vehicle	Slightly disagree
20-34 year	More than 30.000	A free to use vehicle	Neutral
35 or more year		Different	Slightly agree
		I do not drive a vehicle	Very much agree
			Do not know/ no opinion

Secondly, personality traits related to driving, are assumed to have influence on the willingness to release control in a certain driving environment. People with traits of sensation seeking, impulsiveness, and thrill and adventure seeking seem to have the strongest repulsion of automated driving as they are restricted in enjoying these traits. Also, people with a high need of control, extraversion and neuroticism, and self-esteem are assumed to have a particular reaction to automated driving (Saad, 2006; Taubman-Ben-Ari, et al., 2004; Hoedemaeker & Brookhuis, 1998). Therefore these personality traits are measured by giving respondents propositions concerning their driving behavior. These propositions, related with one of the personality traits come from Taubman-Ben-Ari, et al. (2004) If respondents agree with the proposition more than average, they are assumed to have a certain personality trait.

5.6.2 Part 2: View on Intelligent Transportation Systems

Lee and Moray (1994) indicate that people with positive automated systems experience will use a these repeatedly. Hence, the probability of usage increases with the level of familiarity and experience with ITS. Therefore, these factors are used as bench-marks. People with ITS experience are expected to have more interest in these technologies and have more resources available to pay for it. Seven Intelligent Transport Systems are presented to the respondents. Explanation of the systems comes from euroFOT. It describes the systems generally and not based on one vehicle manufacturer (euroFOT, n.d).

- Adaptive Distance Control (replaced for Adaptive Cruise Control, as many people read ACC as cruise control which is not the same).
- Forward Collision Warning
- Speed Regulation System
- Blind Spot Information System
- Lane Departure Warning/Lane Keeping Assist
- Navigation System

As trust also seemed an important factor, this is measured in the experiment. This is done by presenting people propositions which come from Carlson, et al., (2013) and Parasuraman & Riley (1997). These sentences were perceived as having the most influence on someone's trust of an automated system in the automotive domain.

- Information of the effects of the automated vehicle
- Extent of research on the automated vehicle's reliability
- My own understanding of the automated vehicle

Respondents had to give a score to who much they agreed with the particular propositions with a likelihood scale of 1 to 5. Measuring how much they would deviate on average of the mean would give them a mark of how much trust they had in an automated vehicle.

Lastly, to learn respondents more about automated systems having control of driving tasks , they are asked how much they are willing to release the tasks velocity determination, braking and accelerating, route determination and determination of position on the road.

5.6.3 Part 3: choice

The third part consists of the stated choice part, which is based on 8 choice sets. However, as 8 choice sets are too much to handle for a respondent, blocking is used. The first 4 choice sets are represented in the first block and the last 4 choice sets are represented in the second block. Each respondent will be randomly assigned to one of the two blocks. Attributes that will be researched are given in Section 5.2.

5.6.4 Part 4: Socio-demographic and psychographic factors

The socio-demographic factors that are questioned are gender, age, education level and household situation, as described in Table 5.5 . The reason there are studied is because they appeared to have influence in previous research or because their link with automated driving is interesting to research.

Table 5.5: Socio-demographic factors

Gender	Age	Education level	Household situation
Male	Less than 25	No or primary education	Single person household
Female	25-39	Secondary education	Multiple person house-hold with children
	40-54	Lower education (MBO)	Multiple person house-hold without children
	55 of more	Higher education/ university	Different

It appears that consumption behavior is often closely linked to lifestyle. People tend to consume products that they associate with their way of life. With the division of Motivaction, depicted in Figure 5.2, a target user group can be addressed easier with the activities and interest they are assumed to have. Every user group represents a group of people with the same norms and values and are described differently. Within the questionnaire, the division is made by letting people chose a sentence that best reflects their way of living. These sentences come from a report of Drijver & Broer (2013) who write about stimulating sustainable consumer behavior and the role of the government.

Mentality in the Netherlands

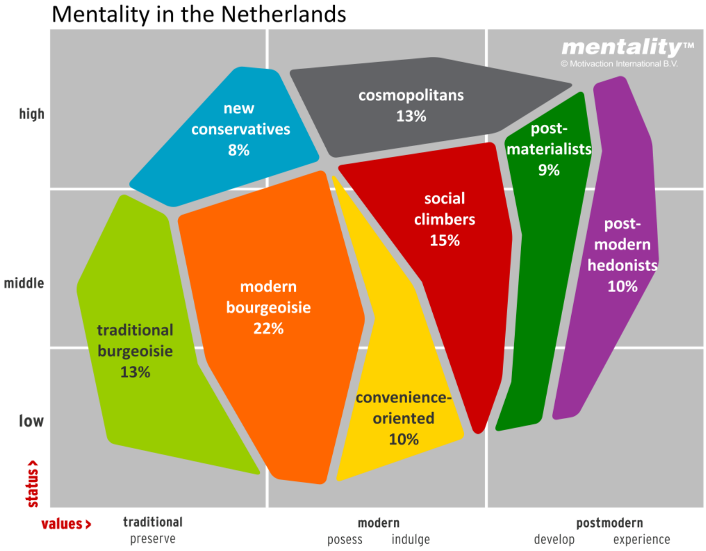


Figure 5.2: Lifestyle division in the Netherlands, according to Motivaction (2012)

5.7 Conclusions

In this chapter the proper steps are given to conduct a discrete choice experiment. This experiment provides data to estimate models which gives insights in the automated driving situations preferred by vehicle users. The questionnaire starts with attracting respondent's attention by asking about their driving experience and if they agreed with certain driving style propositions. In the following parts, the questionnaire focuses more on the subject of automated systems. In the second part, the respondents are asked which ITS they are familiar with and have experience with. Later on, they are informed about systems that take over control of driving tasks and are asked how willing they are to take over four primary tasks. The last question of this part aims at providing insights in how important three trust-factors are for respondents' willingness to use an automated vehicle. The third part of the questionnaire consisted of the stated choice questions. The respondents are randomly divided in one of the two groups. One group is assigned to four particular choice sets, while the other groups is assigned to four other particular choice sets. The choice sets consist of refinement of attributes presented in Chapter 3. Respondents are asked to choose the driving situation that they prefer. They can choose between 3 alternatives. The first two are built up by one level of each attribute, which was previously randomly assigned to the alternative. The third alternative is labeled as 'none of both'. It is assumed that when respondents choose this alternative, they do not prefer to release control of driving tasks. In part 4, respondents are asked to give socio-demographic and psychographic information. Lastly, respondents can give some remarks and then are thanked for their participation. The following chapter describes the data collection and analysis of the experiment.

Chapter 6

Identifying vehicle users' preferences

The set up questionnaire provides data that enables modeling the choice behavior of respondents. This chapter describes the data collection approach in Section 6.1. Next, Section 6.2 continues with a descriptive analysis of the obtained data. In this section, insight is provided in respondents' background. With this knowledge, interesting user groups for further research are determined and explained in Section 6.3. The insights described by three choice models are given in Section 6.4 to 6.6. Section 6.7 provides an overview of the found results.

6.1 Data collection

Two approaches are applied to invite respondents for this questionnaire. The first approach was to address an Internet panel of the market agency PanelClix[2]. This resulted in 524 complete responses. The other way was though personal and business network. A hyperlink to the survey was sent via e-mail and spread via social media. This second approach resulted in 149 complete responses. Hence, in total the data set consists of 673 respondents.

A rule of thumb by Orme is used to calculated the desired number of respondents. According to Rose & Bliemer (2013) this is the most commonly cited rule of thumb to calculate stated choice study sample size requirements.

$$N \geq \frac{500\ L^{max}}{J*S} \qquad (17)$$

Where
L^{max} is the largest number of levels of any of the attributes;
J is the number of alternatives per choice set;
S is the number of choice sets.

Within this experiment, L^{max} is 4; *J* is 3; and *S* is 4. Therefore the desired minimal number of respondents is 167. However, for this experiment the needed number of respondents has to be multiplied by 2, as there are two blocks of respondents that both are four times presented with different choices sets. Thus, in this experiment a minimum of 334 responses is desired. In the present study, 673 complete responses are obtained, which is sufficient to the rule of thumb. It is assumed that this number is also sufficient to analyze the differences between target groups.

6.2 Descriptive analysis

This section describes information drawn from the data of the experiment. Information is presented about how user characteristics are divided over the sample, the differences in

[2] http://www.panelclix.com

familiarity with ITS, the degree of influence several factors have on trust in automated systems. Additionally, a description of which user groups are likely to prefer automated driving and which groups do not is provides.

6.2.1 Description of research sample

The results of this experiment are based on answers from 673 respondents. Table 6.1 illustrates characteristics of the target group and the resulting sample.

Table 6.1: Characteristics of the sample and target group[1]

User group	Target	Research sample
Gender[2]		
Male	53%	51%
Female	47%	49%
Age[1]		
18-24	9%	17%
25-39	25%	35%
40-54	31%	47%[3]
55 +	35%	
Education[4]		
Primary education	8%	1%
Secondary education	33%	12%
Lower education (MBO)	30%	34%
Higher education/university	29%	54%
Household situation		
Single person household		18%
Multiple person household with children		40%
Multiple person household without children		37%
Driving experience		
Less than 5 year		16%
5-19 year		40%
20-34 year		25%
35 or more year		19%
Kilometers per year		
Less than 10.000		37%
10.000-30.000		47%
More than 30.000		13%

[1] The total sample of the different characteristics is not always 100%. This is caused by rounding-off, or because respondents indicated that they did not know the answer to the question, or because they indicated that their suiting option was not in the option list.
[2] Target group is defined by people in the Netherlands that own a passenger driver's license in 2012 (SWOV, 2012c);
[3] Age divisions of this thesis and SWOV did not correspond, therefore 40-54 and 55+ are gathered;
[4] Target group is defined by degree of education of people between 15 and 65 years old (CBS Statline, 2013).

6.2.2 Further insights

Besides the description of the sample group, also insights are obtained concerning how familiar males and females and people of different ages are with ITS. In addition, the importance of three trust-factors is described. Lastly, the willingness to release control to automated systems per user group is described.

When relating the level familiarity of ITS with gender and age, it appears that males know more ITS than woman. The Chi-square calculation matrix can be found in Appendix IV. This matrix also shows that females of 40 or older know less ITS than the average sample. As ITS are closely linked to systems in automated vehicles, the following assumption is made: it is assumed that the probability that males will come in contact with automated driving is higher than the that females will come in contact with automated driving.

Next, also insights are gained in the importance for vehicle users to use automated vehicles, concerning three trust-factors. Firstly, of the total sample, 37% of the respondents denote that information of the effects of the automated vehicle is important to very important for them to ride in these vehicles. Secondly, 50% of the respondents indicate that their own understanding of the automated vehicle is important to very important for their willingness to use it. Thirdly, 43% of the respondents agree that the extent of research on the automated vehicle's reliability is important to very important for their willingness to use automated vehicles.

Furthermore, within the stated choice questions, respondents could choose for 'none of both' when they were not willing to drive in the given driving situations. When respondents chose four times for 'none of both' but have seem to answer other questions with care, it is assumed that these respondents do not prefer automated driving. This category contains 60 respondents. Valuable insights can be drawn from descriptive of this category as it estimates which people not tend to use automated driving possibilities in real life. It has to be taken into account that the some groups within the sample are rather small, therefore these numbers are only seen as an indication of which user groups do, and which groups do not prefer automated driving. An elaborated overview can be found in Appendix V. and a concise overview is presented in Table 6.2. A '+' indicates that the user group within a the sample is on average willing to release control of driving tasks to automated systems. A '-' indicates that the particular user group is not willing to release control.

Tables 6.2 shows that males and young respondents are more willing to cede driving tasks, than females and older respondents. Furthermore, there is significant difference in the willingness of higher educated respondents to release control, compared to lower educated respondents. Respondents with most driving experience are least willing to release tasks. The years of driving experience could be in accordance with age, which explains the same trend of willingness. Respondents with much familiarity as well as experience with different ITS, are more willing to release control. Furthermore, as indicated by previous research, people with low trust in automated vehicles do not chose to use automated systems, while people with high trust are preferring automated driving. Additionally, it is striking that respondents with a high need for control seem to prefer automated driving more than respondents with a lower need for control.

Table 6.2: Willingness to release control

User groups		Chi-square	p<0,05
Gender			
Male	+		
Female	-		
		7,784	*
Age			
18-24	+		
25-39	+		
40-55	+		
55+	-		
		17,045	*
Education			
Primary education[1]			
Secondary education	-		
Lower education (MBO)	-		
Higher education/university	+		
		20,659	*
Household situation			
Single person household	+		
Multiple person household with children	+		
Multiple person household without children	-		
		4,104	
Driving experience			
Less than 5 year	+		
5-19 year	+		
20-34 year	+		
35 or more year	-		
		16,074	*
Kilometers per year			
Less than 10.000	-		
10.000-30.000	+		
More than 30.000	+		
		2,750	

User groups		Chi-square	p<0,05
ITS familiarity			
Low	-		
High	+	**16,880**	*
ITS experience			
Low	-		
High	+	**11,649**	*
Trust			
Low	-		
Average	+		
High	+	**21,914**	*
Personality traits			
Self-esteem			
High	+		
Low	-	**0,114**	
Need for control			
High	+		
Low	-	**6,059**	*
Sensation seeking			
High	-		
Low	+	**0,530**	
Extraversion			
High	-		
Low	+	**4,049**	*

[1] Chi-square condition is violated: expected value is below 1 (Cochran, 1954)

6.3 Model analysis

Several user characteristics are found to explain possible differences in the willingness to release control of driving tasks. These characteristics are gender, age, education, driving experience, familiarity and experience with ITS, trust and two personality traits. Because of time constraints, not every characteristic can be researched in depth. According to the previous literature, gender and age are predicted to explain differences in preferences. Taking in account that these are the most easily addressable and identifiable user characteristics, gender and age will be further researched. In addition, the preferences of respondents with different experiences with ITS and different education levels will be further researched. These user groups are assumed to explain differences in willingness to cede driving tasks.

This present research is about choice data. This means that an alternative is chosen or not chosen and therefore results in binary data (i.e. 0 or 1). The chosen alternative is the one that produces the highest level of utility, or the least amount of negative utility. There is no direct information about the order of preferences. But with repeated observations, it is possible to collect enough information of the preference formation.

To be able to estimate the preferred levels of attributes in the models, the attribute-levels were coded. This is done by effect coding (Hensher, et al., 2005). This means that *n* levels of the attributes are coded by *n*-1 indicator variables. The *n*-1 levels are coded 1 on the corresponding indicators and coded 0 on all other indicator variables. The last *n* level is coded -1 for all indicator variables.

In this research, a NLOGIT Version 5 is used to estimate the parameters of the choice models. From the results of the choice sets, the utility of each alternative can be estimated. For every attribute-level, parameter β can be estimated. β_0 defines the base alternative. With the 'none of both' alternative nothing is known of its attributes and levels and therefore this alternative is coded by zero's. When analyzing the β_0 insights in the 'none of both' utility is gained (Marchau, et al., 2001). To derive the part-worth utilities of the attribute-levels, the parameters are multiplied with the coded values as can be seen in Table 6.3.

Table 6.3: Calculation of example part-worth utilities (v_{ijk})

Attribute level	**First indicator variable**	**Second indicator variable**	**Third indicator variable**	**Derived part-worth utility**
Level 1	1	0	0	β_1* 1 + β_2* 0 + β_3* 0
Level 2	0	1	0	β_1* 0 + β_2* 1 + β_3* 0
Level 3	0	0	1	β_1* 0 + β_2* 0 + β_3* 1
Level 4	-1	-1	-1	β_1* -1 + β_2* -1 + β_3* -1

In Appendix VI, a correlation matrix of the estimated levels is given. This matrix shows that there are no significant correlations between levels of different attributes.

6.4 Multinomial logit

The most basic model, the Multinomial logit model, is a model which presents the user's preferences, assuming that the error terms (ε_i) are identically and independently distributed. The Likelihood ratio of the model is 301,289 and therefore the estimated parameters fit significantly better than the model with no parameters. However, as can be seen in Appendix VII, this model's pseudo R^2 is only 0,051 and therefore the model fit is very weak. Hence, this research will not further go into more specific estimates of the Multinomial logit model. According to theory, the Latent class model's predictive power is higher. Therefore, the next section will describe the application of the Latent class model, which is used to find unobservable heterogeneity with latent class division.

6.5 Latent class model

The Latent class model is assumed to have a better model fit as the Multinomial logit model as heterogeneity among respondents is taken in account by grouping respondents with similar observable parameter distributions into different classes. The probability that the respondent has a certain user-characteristic, is considered. With this information, it can be calculated what the probability it is that a respondent with certain characteristics belongs to a group with certain preferences for automated driving.

As indicated in Section 6.3, it is interesting to further go into the preferences differences between male and female and respondents from different age groups. Therefore, these user-characteristics are included as parameters. As the same individual is observed in four different choice situations, the data in NLOGIT is used as panel data.

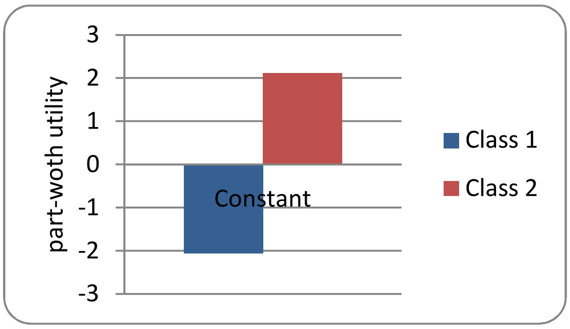
6.5.1 Model for gender and age

First, the number of classes is determined. This is done by comparing the model fit of different classes. The estimated model with the best fit will be further researched. Hereby it has to be taken into account that the higher the number of classes, the lower the number of respondents and therefore the less representative the class is. For this reason, only 2 to 7 classes are estimated. For comparison the proposed information criteria as introduced in subsection 4.5.3 are used. In Table 6.4, an overview of the information criteria outcomes and the adjusted R^2 value is given for models with 2, 3, 4, 6 and 7 classes. A model with 5 classes has an estimated variance matrix of estimates which is singular, and is therefore is not included in this overview. All other models have a quite well model fit and therefore are all an improvement over the Multinomial logit model.

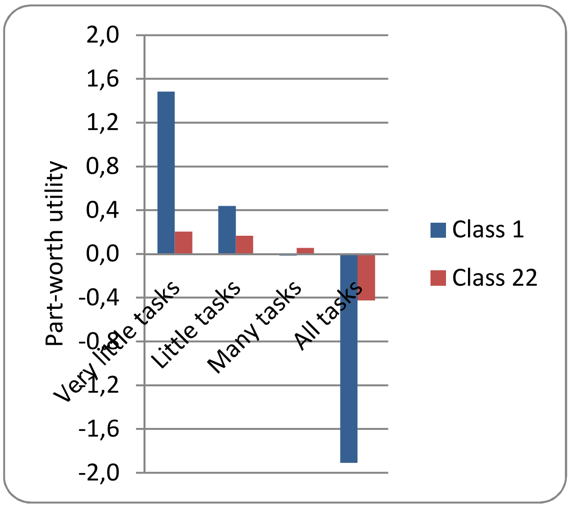
Table 6.4: Model fit parameters for 2-7 classes

# classes	LL_M	LL_0	# parameters	R^2ajd	AIC	BIC
2	-2479,23381	-2957,46430	27	0,152573	5012,468	5171,715
3	-2432,68847	-2957,46430	42	0,163240	4949,377	5197,095
4	-2434,80018	-2957,46430	57	0,157454	4983,600	5319,789
5						
6	-2387,30132	-2957,46430	87	0,163371	4948,603	5461,732
7	-2371,71485	-2957,46430	102	0,163569	4947,430	5549,030

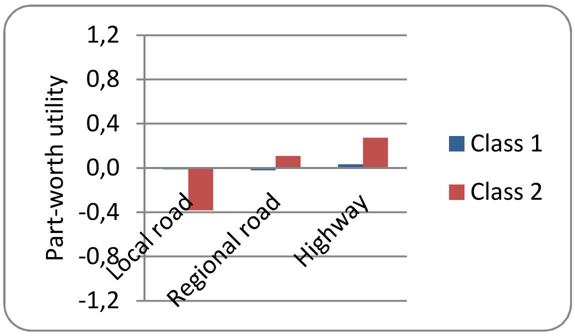
The BIC value is lowest with the lowest number of classes. The AIC value seems to increase with a higher number of classes, but also is low with a model with 3 classes. The adjusted R^2 follows the same pattern as AIC. As compared to all other models, the model with 2 classes includes the most significant individual parameters. Besides, the AIC tends to overestimate the number of classes. Therefore, a model with two classes will be further researched. The part-worth utilities of the attributes per class are presented in Figure 6.1a-g. An overview of the part-worth utilities in numbers is given in Appendix VIII.



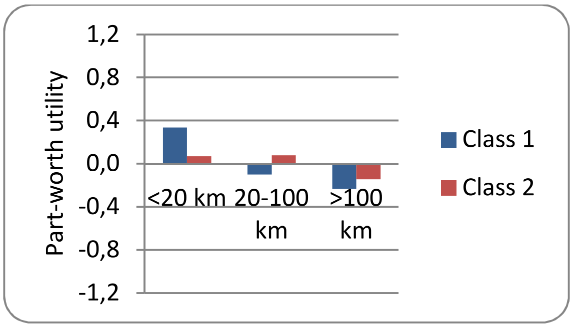
a: Constant of Latent class model



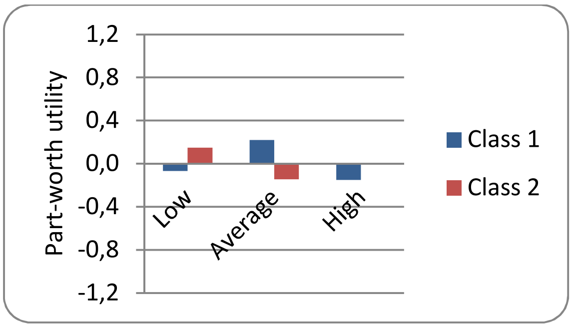
b: Effect of attribute *level of released driving tasks*



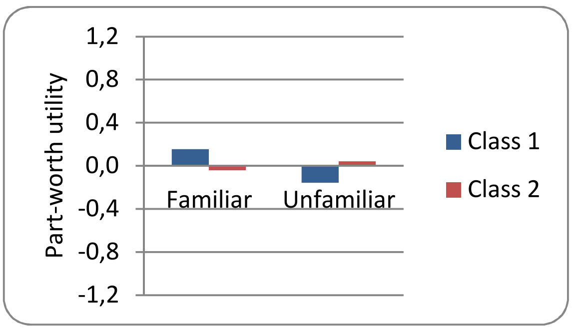
c: Effect of attribute *road type*



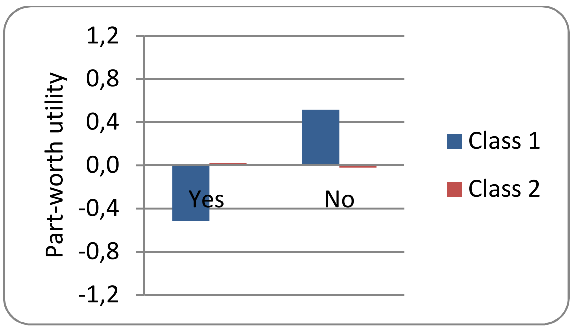
d: Effect of attribute *length of trip*



e: Effect of attribute *density on road*



f: Effect of attribute familiarity with route



g: Effect of attribute *secondary task*

Figures 6.1a-g: Effects of the constant and attributes of LC model

To characterize the two different classes, also the relative importance of the attribute in relation to the overall importance is calculated. This is done by measuring the range between the highest and lowest parameter value per attribute. This range is then divided by the sum of the ranges of all attributes in order to derive a percentage (Marchau, et al., 2001). The result is depicted in Figure 6..

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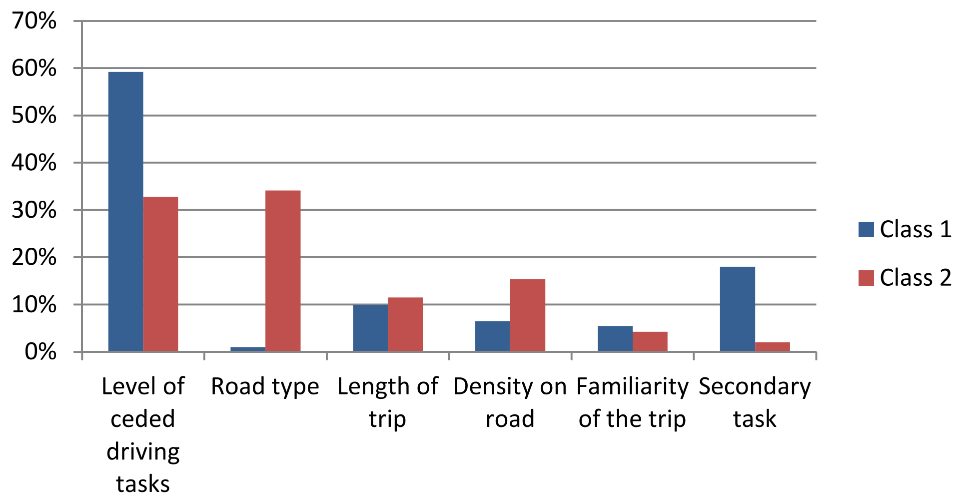


Figure 6.2: Relative importance of attribute for two latent classes

As can be seen from Figure 6.1, the constant of class 1 is very negative. From this it is assumed that class 1 is not so willing to drive with automation. Also, Figure 6. shows that the level of released tasks and the secondary task are very important for class 1, compared to other attributes. Within these attributes respondents do not want to give high control to the vehicle or perform other tasks while focusing on driving. This group is therefore labeled as the less-potential users. In contrast, the constant of class 2 is positive. Compared to class 1, class 2 does not find the attribute secondary task important. Their willingness depends on the level of released control of driving tasks and the road type. Although they are not positive about full automated driving, this negative contribution to the structural utility is not so high as with class 1. They prefer to release control on a highway. Because of this more positive attitude, this class is referred to as more-potential users.

As calculated with Equation 5 from Chapter 4, it is indicated that the probability to be in class 1 is 27%. For class 2 this probability is 73%. The probabilities to be either in class 1 or 2 can be depicted from Table 6.5. From this table it appears that the probability that males belong to the more-potential users class is higher than the probability that woman belong to this class. Also, it is seems that young people have more probability to be in the more-potential users group than old people. However, for both user groups the differences are not so big.

Table 6.5: Probability of belonging to a class with characteristic z

	Class 1	Class 2
18-39	23%	77%
40+	32%	68%
Male	22%	78%
18-39	18%	82%
40+	26%	74%
Female	34%	66%
18-39	29%	71%
40+	40%	60%

6.5.2 Scenarios from the Latent class model

With these estimates, the probability an individual with certain characteristics chooses one driving situation over the other is calculated, taking into account the probability that the individual belongs to one of the two classes. As an useful example, two driving situations are compared, as shown in Table 6.6. The first driving situation is one that is assumed to be currently available and useful for people who are willing to spend some resources on their vehicle purchase. This is based on ACC, where level 1 tasks should be released and which is used on highways with low density. For the second driving situation, a more intervening situation is proposed: all control of driving tasks are released on a regional road with high density. The length of the trip, the familiarity with the route and whether or not to perform a secondary tasks is the same for both driving situations.

Table 6.6: Structural utilities of two driving situations of the LC model

Driving situation 1	**Utility**		**Driving situation 2**	**Utility**	
Available on current market	Class 1	Class 2	Intervening sit.	Class 1	Class 2
Constant	-2,06937	2,11394	Constant	-2,06937	2,11394
Very little tasks released	1,48349	0,20433	All tasks released	-1,90742	-0,42615
Highway	0,03517	0,27502	Regional way	-0,02162	0,10761
Trip of 20-100 km	-0,09960	0,07609	Trip of 20-100 km	-0,09960	-0,09960
Low density on road	-0,06967	0,14916	High density on road	-0,15040	-0,00311
Familiar with trip	0,15579	-0,04116	Familiar with trip	0,15579	0,15579
No secondary task	0,51502	-0,01954	No secondary task	0,51502	-0,01954
Total	**-0,04917**	**2,75784**	**Total**	**-3,57760**	**1,82894**

From Equation 6 is calculated that the probability that a young male with a certain probability to belong to class 1, will chose driving situation 1 is 17%, with $P_{i|c}$ = 97%. With the same steps, more probabilities can be calculated as can be seen in Table 6.7. Between brackets the probability of choosing alternative *i*, given the class *c* is presented. This table indicates that there is a 28% probability that people prefer the intervening situation when they are in the group of the more-potential users of automated driving.

Table 6.7: Probability of an individual with a certain probability to belong to a class, chooses a driving situation

Probability		young males	old males	young females	old females
Driving situation 1					
class 1	with $P_{i\|c}$ is (97%)	17%	25%	28%	38%
class 2	with $P_{i\|c}$ is (72%)	59%	53%	51%	43%
Driving situation 2					
class 1	with $P_{i\|c}$ is (3%)	1%	1%	1%	1%
class 2	with $P_{i\|c}$ is (28%)	23%	21%	20%	17%

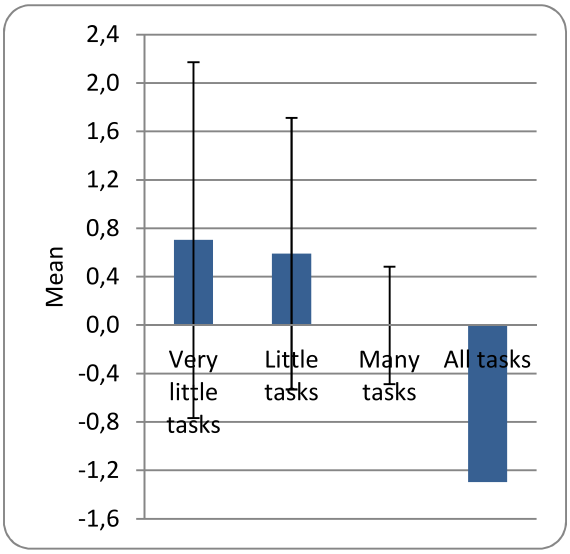
The Latent class model has provided some insights in the taste heterogeneity among two different classes. It can be concluded from this model that within the sample, there is high taste heterogeneity and that different user groups prefer different driving circumstances. A more flexible model that reveals sources of taste heterogeneity by estimating the range of each utility weight in the sample is the Mixed logit model. This model will be elaborated in the next section.

6.6 Mixed logit model

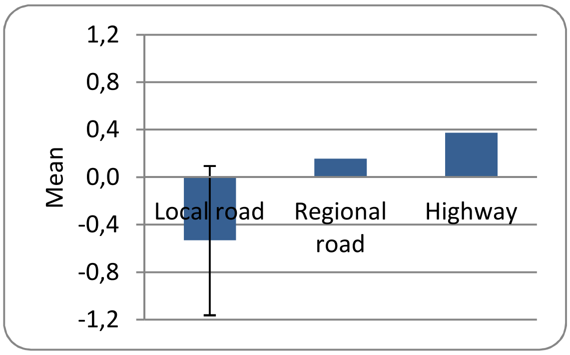
Compared to the Multinomial and Latent class model, the Mixed logit model allows the β_n to be different for each person and therefore reveals taste heterogeneity among the sample. The ML model shows insights in the parameters of the distribution of β_n, such as the mean and standard deviation.

6.6.1 Overall sample

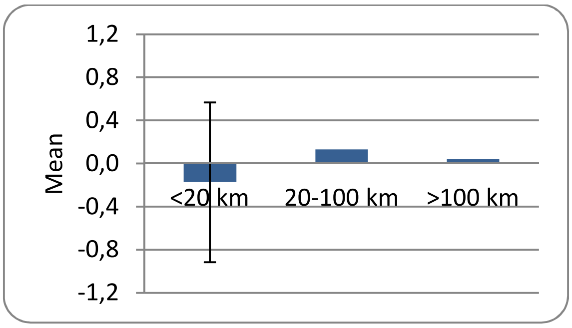
First, the overall model's parameters are estimated in NLOGIT. As for the LC model, for this model the same individual is observed in several choice situations and therefore the data in NLOGIT is used as panel data. in addition, 1000 Halton draws were applied in NLOGIT as this can reduce simulation time while the effectiveness will not be reduced (Train, 2009). According to Borgers, et al., (2010), with this number of Halton draws, the parameters become more significant. All standard deviation parameters of all attributes were included, applying normal distribution. The standard deviations which were not significant are deleted. After the deletion of these standard deviations, the model was estimated again. The deletion and model estimation was repeated until a model with significant standard deviations was determined. The result can be seen in Appendix IX. This model has an adjusted R^2 of 0,164, a small improvement of the Latent class model. As can be seen in Figures 6.3a-f, the estimated standard deviation of the attributes level of released control driving tasks and road type are significant. The length of trip has also a significant standard deviation. For these attributes it is assumed that there is high heterogeneity.



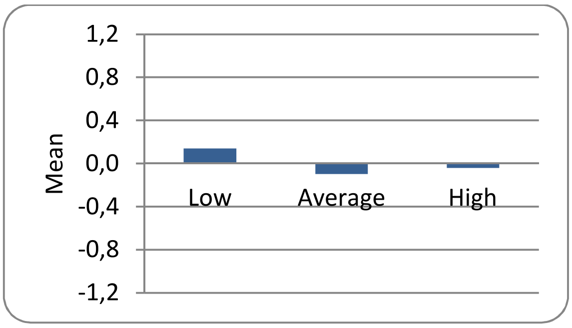
a: Effect of attribute *level of released driving tasks*



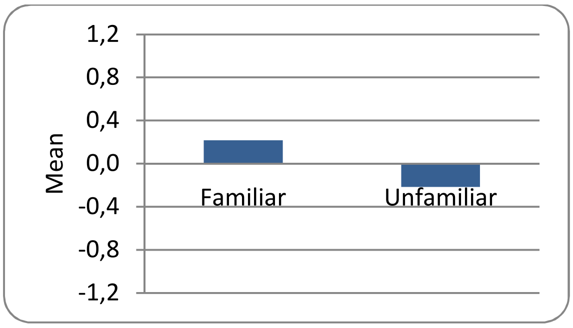
b: Effect of attribute *road type*



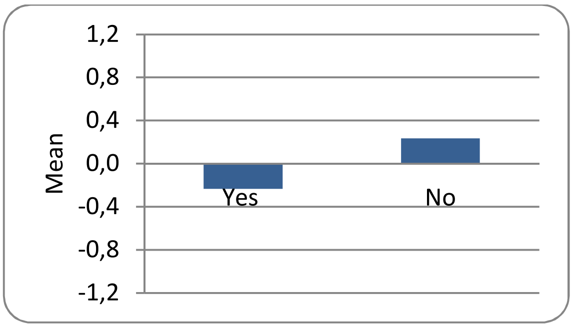
c: Effect of attribute *length of trip*



d: Effect of attribute *density on road*



e: Effect of attribute *familiarity with route*



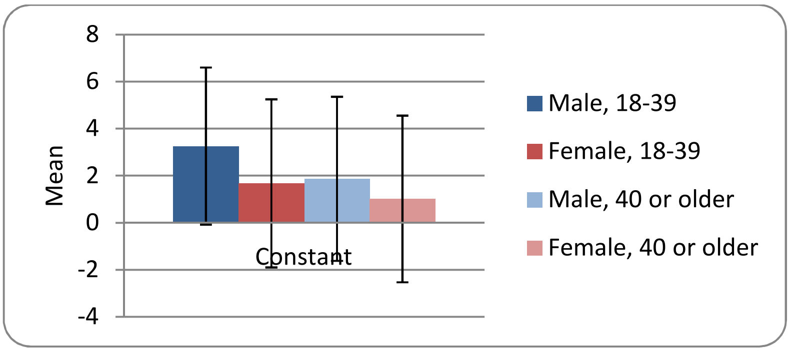
f: Effect of attribute *secondary task*

Figures 6.3a-f: Effects of the constant and attributes of ML model for overall sample

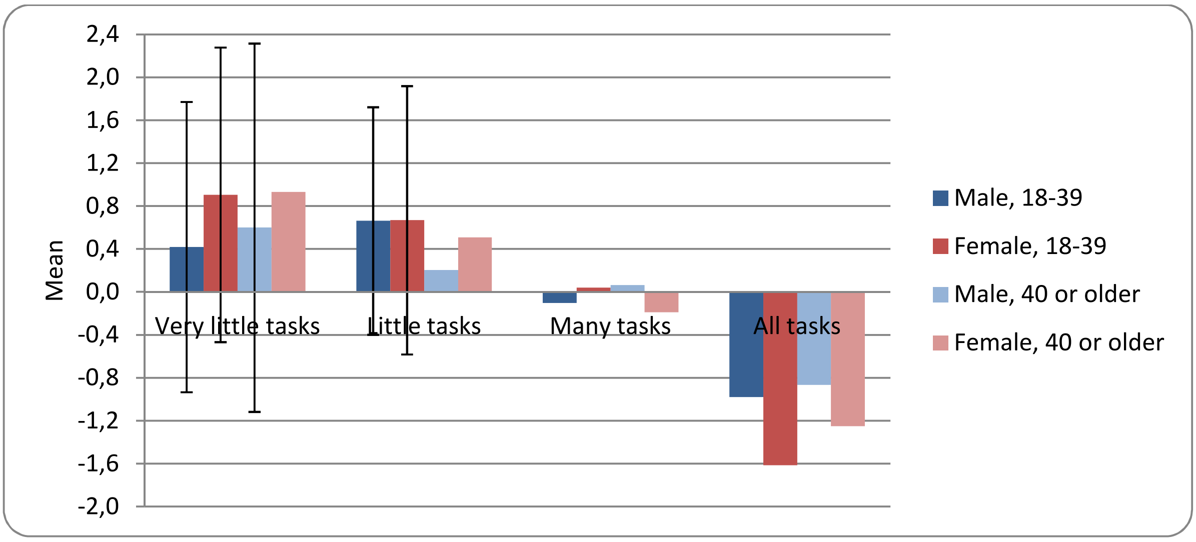
The Figures 6.3a-g give the mean of every attribute-level and the standard deviation when significant. The attributes with significant standard deviation indicate that the parameters vary in the population, i.e. there is random variation across the included respondents (Train, 2009). It can be seen that for the attribute level of released tasks, there is much taste heterogeneity. Within the population, also around one-third is not so positive about releasing control of a very low number of driving tasks (half of one standard deviation plus the rest that is below the mean). From the road type attribute it appears that around four-fifth of the population places a negative value on the local road (half of the sample plus almost one deviation from the mean).

6.6.2 Gender and age

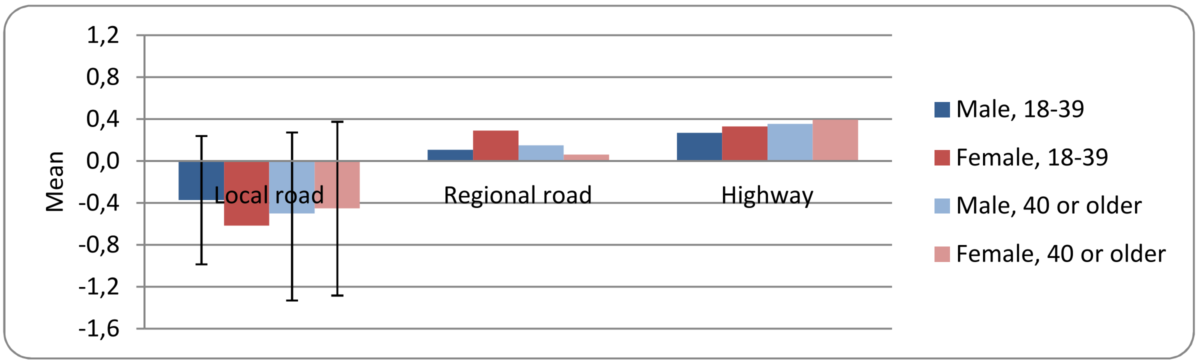
From literature it seems that males and females have another attitude towards automated driving. The same goes for younger and older people. To get insights in preferences and taste heterogeneity within combinations of this user characterization, Mixed logit models are presented. Again, the deletion of non-significant standard deviations is applied, which results in the Figures 6.4a-g. The results in table format can be found in Appendix X and XI. The adjusted R^2's for the models with males and females between 18 and 39 years old, males and females of 40 year or older, respectively 0,161; 0,165; 0,137; 0,171. This implies that the models predict the data quite well. The preferences of the different age and gender categories are quite similar.



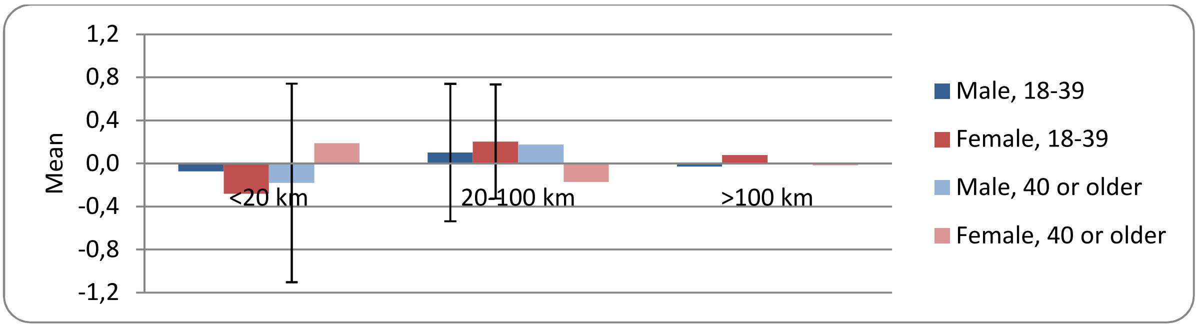
a: Effect of constant



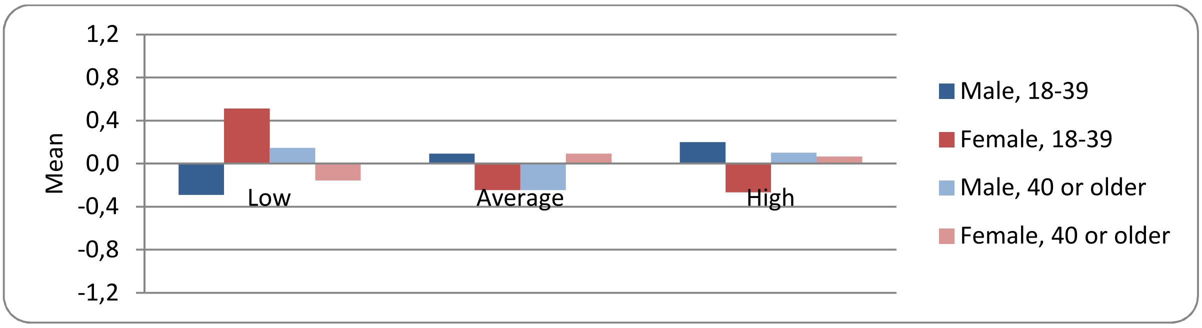
b: Effect of attribute *level of released driving tasks*



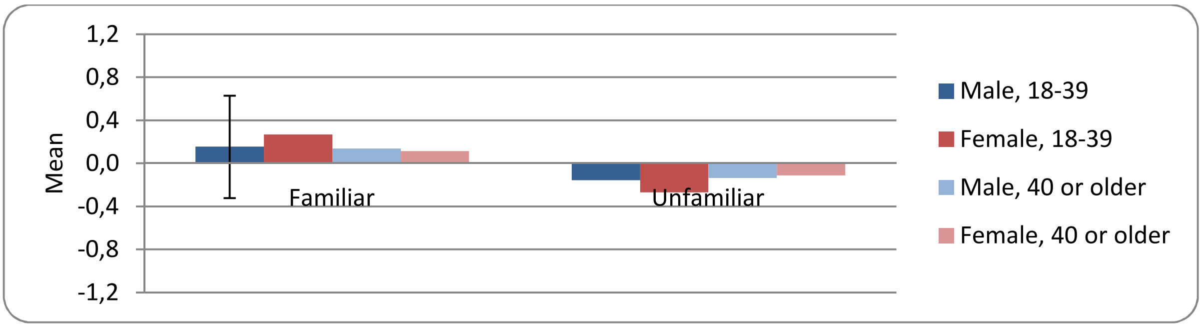
c: Effect of attribute *road type*



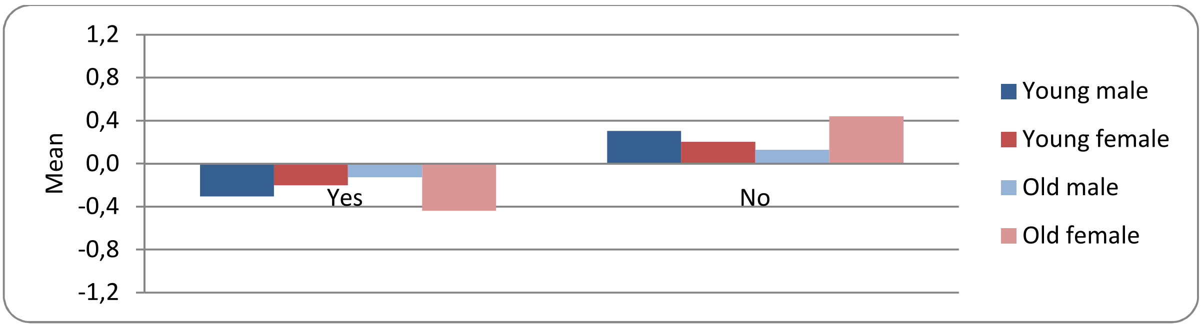
d: Effect of attribute *length of trip*



e: Effect of attribute *density on road*



f: Effect of attribute *familiarity with route*

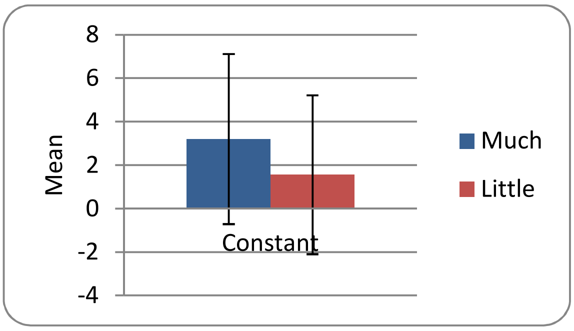


g: Effect of attribute *secondary task*

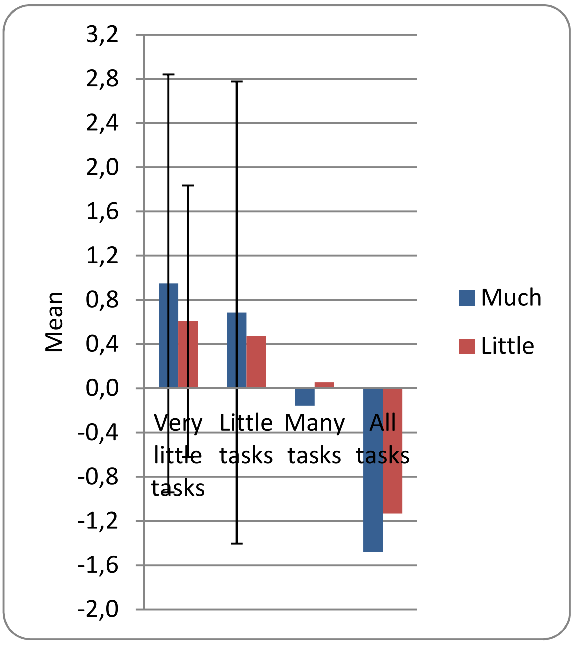
Figures 6.4a-g: Effects of the constant and attributes of ML model for gender and age

6.6.3 Different experience levels of ITS

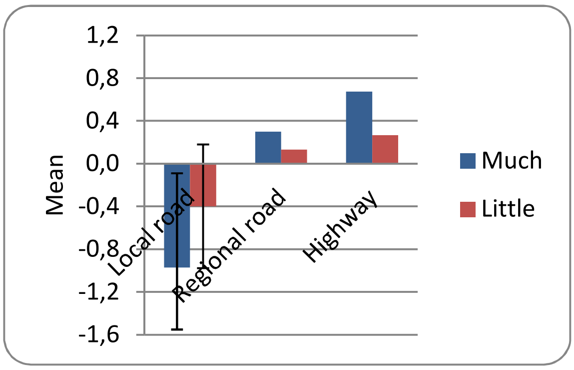
The experience respondents have with ITS seems to predict the willingness to cede driving tasks. The next models should give insights in the preferences of respondents who have experience with many ITS and respondents who did not use any or did not use so many ITS. The model *much experience* has an adjusted R² of 0,176 and the model *little experience* as an adjusted R² of 0,159. Hence, both predict the data well. The effects per attribute can be found in Figures 6.5a-g (in table format in Appendix XII).



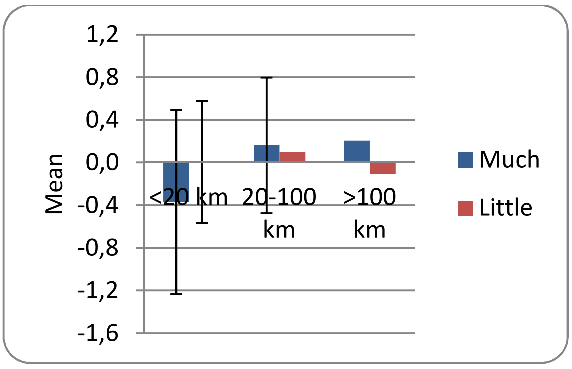
a: Effect of the constant



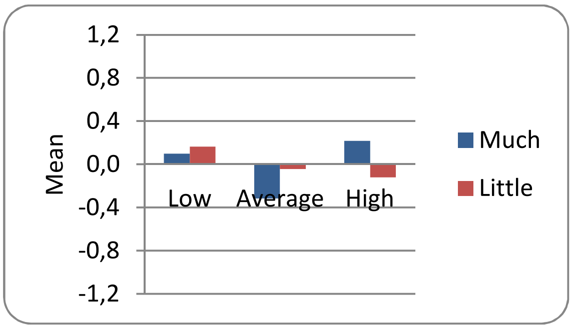
b: Effect of attribute level of released driving tasks



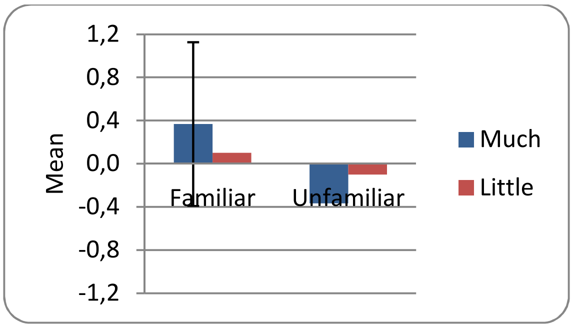
c: Effect of attribute *road type*



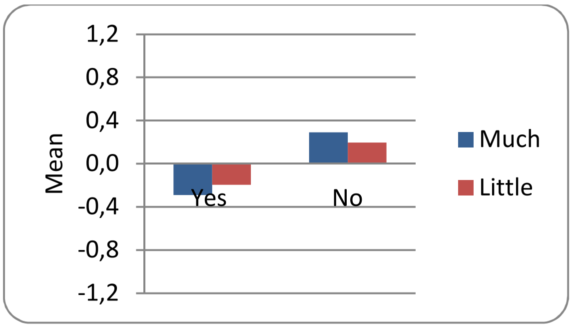
d: Effect of attribute *length of trip*



e: Effect of attribute *density on road*



f: Effect of attribute *familiarity with road*



g: Effect of attribute *secondary task*

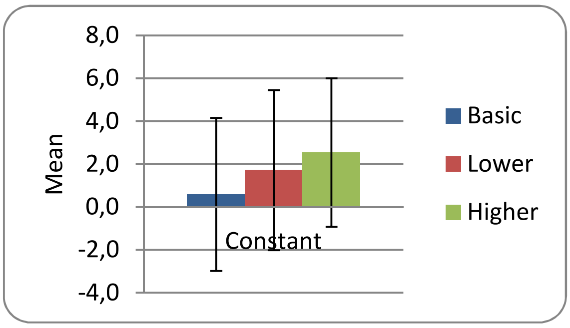
Figures 6.5a-g: Effects of the constant and attributes of ML model for ITS experience

The figures show that both user groups have almost the same preferences. However, respondents who are more experienced with different ITS are more explicit in their attitude towards attributes of automated driving. Although both groups of respondents show on average to be positive about a only releasing one or two primary tasks, the standard deviation indicates of group with much experience that there are also respondents that are negative about only releasing on or two primary tasks. Both groups prefer to drive automated on highways and are not willing to perform a secondary task during automated driving. Experience ITS vehicle users prefer to use the automated driving possibility when they are familiar with the trip they are making.

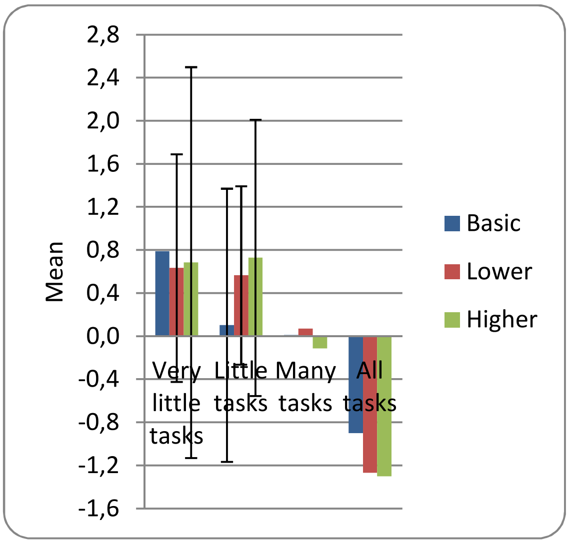
6.6.4 Different education levels

Lastly, Mixed logit models are created by differentiating respondents by their education level. Rogers (2003) indicated with his theory of Diffusion of Innovations that the successive groups adopting new technology, can be described by different characteristics. Vehicle users with advance education are assumed to use automated systems more early than vehicle users with a lower education level. As the group with no or only elementary education is small, this group is joined with the group with only secondary education. For now this combined group will be labeled 'basic education'. Results of a Mixed logit analysis are shown in Figures 6.6a-g (in table format in Appendix XIII). The model for basic education has an adjusted R^2 of 0,118; the model for lower education an adjusted R^2 of 0,158; and the model for higher education/university has an adjusted R^2 of 0,176. The predictive power of the lower as well as higher education model is therefore quite strong, while the predictive power of the basic education model is not so strong.

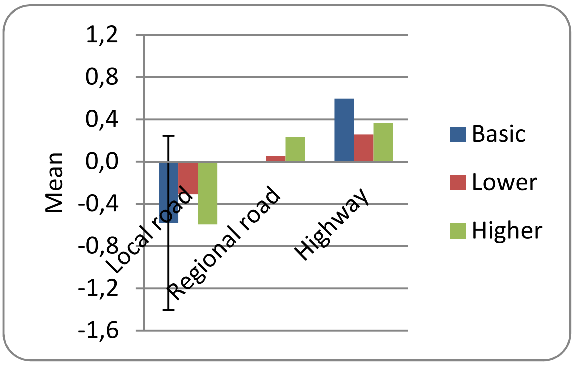
Also for this characterization, respondents seem to agree on average on the level of release tasks, road type, familiarity with route and secondary tasks preferences. However, respondents with basic education are only willing to release very little tasks. Respondents with higher education are most willing to release control. In contrast with basic and lower education, respondents with high education are more willing to cede driving tasks in dense traffic circumstances.



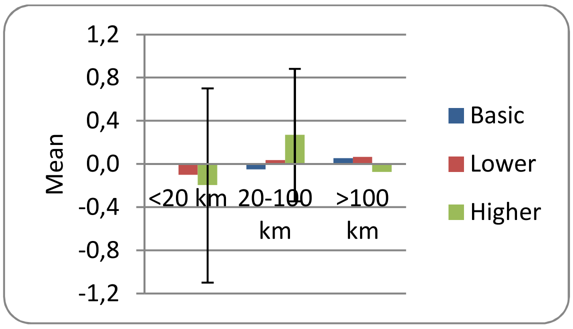
a: Effect of the constant



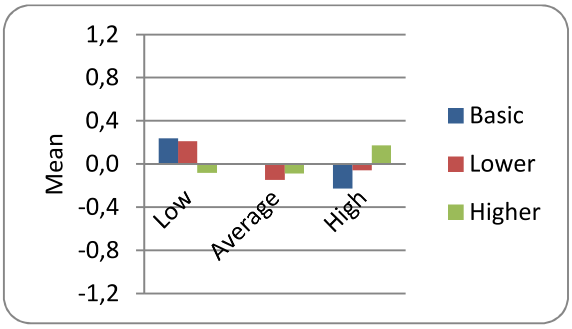
b: Effect of attribute *level of released driving tasks*



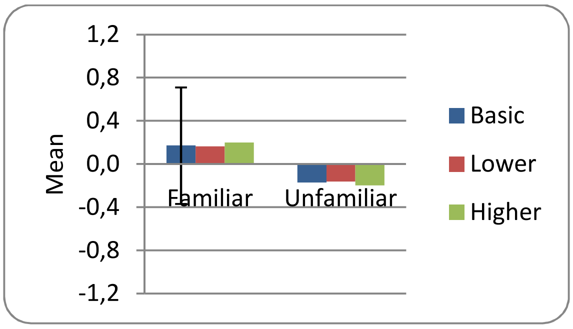
c: Effect of attribute *road type*



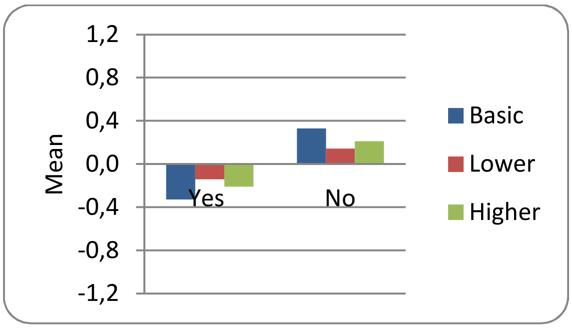
d: Effect of attribute *length of trip*



e: Effect of attribute *density on road*



f: Effect of attribute *familiarity with the route*



g: Effect of attribute *secondary task*

Figures 6.6a-g: Effects of the constant and attributes of ML model for education level

6.6.5 Scenarios from the Mixed logit model

The same scenario as used with the Latent class model is shown in Table 6.8 and used to calculate the choice probability concerning the overall sample. This is calculated by simulating the normal distributions for each parameter drawing random values a 1000 times. The probability that the intervening driving situation is chosen over the currently available alternative is 15%.

Table 6.8: Mean and standard deviation of two driving situations of the ML model

Driving situation 1			**Driving situation 2**		
Available on current market	Mean	St. dev.	Intervening sit.	Mean	St. dev.
Constant	2,06009	3,78225	Constant	2,06009	3,78225
Very little tasks released	0,70429	1,46979	All tasks released	-1,29570	
Highway	0,37461		Regional way	0,15712	
Trip of 20-100 km	0,13135		Trip of 20-100 km	0,13135	
Low density on road	0,13807		High density on road	-0,04094	
Familiar with trip	0,21759		Familiar with trip	0,21759	
No secondary task	0,21778		No secondary task	0,21778	

6.7 Conclusions

With an online questionnaire, 673 complete responses from vehicle users with a passenger vehicle driver's licenses are collected. This complies with the required sample size. Gender and age are quite well distributed over the sample. More than half of the respondents have attainted higher education or university. Differences in gender, age, education level, driving experience, familiarity and experience with ITS, trust and some personality traits seem to determine the differences in willingness to release control. Gender and age are further differentiated in the discrete choice models as they are most addressable for stakeholders to apply a certain strategy for. Furthermore, models for experience with ITS, and education level are examined. User groups within these characterizations are assumed to be the first to be willing to cede driving tasks.

The Multinomial model has a low goodness of fit and therefore is not further examined. The Latent class model and the Mixed logit model show considerable statistical improvements over the Multinomial logit model. The models' fit are comparable and both offer different benefits. The Latent class model implies that the class which is most willing to release control, finds the road type relatively important. Making automated driving available on highways can contribute to user's willingness. The probability that a male belongs to this group is slightly higher than the probability that a female belongs to this group. Moreover, the probability that an individual between 18 and 39 years old belongs to this group is slightly higher than the probability that an individual of 40 year or older belongs to this group.

From the Mixed logit model for the total sample, it appears that there is high taste heterogeneity among the sample for the attributes level of released driving control, road type and length of trip. With Mixed logit models with distinguished user groups it is aimed to explain this heterogeneity. However, models for gender, age, ITS experience and education level do not seem to clarify the heterogeneity. User groups within these models seem to have comparable preferences. Therefore, first the corresponding results are described. Later on, the differences will be explained.

The models indicate that the effect of the level of released driving tasks is very high. It seems that on average, .vehicle users are only positive about releasing very little or little control of tasks. They do not prefer to release control of all tasks and are neutral about releasing many tasks. Moreover, vehicle users want to release control on highways and are neutral to little positive about ceding driving tasks on regional roads. They do prefer to use the systems on local roads. The length of the trip does not contribute much to the willingness to release control. The same is valid for the density on the road. Familiarity of the road and not performing a secondary tasks contribute slightly to the willingness of vehicle users to release control.

Some striking results can be observed. Firstly, the model with gender and age shows that males prefer to release control on dense roads, while female prefer this on open roads. Moreover, higher educated people also prefer to cede driving tasks on dense roads, while lower or basic educated people prefer this on open roads.

Chapter 7

Conclusions and recommendations

This chapter presents the results of this research and thereby it answers the research questions. In Section 7.1, conclusions are drawn by the first answering the sub-questions and thereafter the main question. Section 7.2 presents managerial recommendations.

7.1 Conclusions

Highly beneficial effects for society could be achieved by automated driving. The achievement of these societal benefits require usage of automated driving systems. Usage of automated driving systems implies that vehicle users release control. However, vehicle users have less trust in automated systems than in their own capabilities and therefore it is not granted that they are willing to release control in all driving situations. This has impact on the transport and market planning of stakeholders who want to improve safety, traffic flow, and environmental savings. Therefore this research aims at getting insights in which level of automation and which driving circumstances contribute to the willingness of different vehicle user groups to release driving control. In order to gain these insights, firstly the research sub-questions will be answered.

> *What is automated driving and what are current and expected technological capabilities?*

In terms of automated driving, and current and expected technological capabilities, literature has provided the following insights. Automated driving is enabled by systems in vehicles and infrastructure that can take over control of driving tasks. Information and communication technology, as well as sensors, radars, scanners, cameras etc, form the basis of a vehicle that can drive without human involvement. Therefore, an automated vehicle refers to a vehicle in which control of driving tasks is performed by a machine. Control of driving tasks can be taken over to different degrees, from no systems having no active control, to systems which have fully automated control. BASt expert group has identified five levels: driver only, assisted driving, partial automation, high automation, and fully automation. Besides the control systems have over the driving tasks, the levels differ in the drivers required monitoring level, and the required readiness to take over control in critical situations. Currently, only systems that provide assisted driving or partial automation are available on the market, these include systems that allow automated braking and accelerating, automated emergency braking, automated steering, automated congestion driving, and systems that allow the vehicle to maintain between road lanes. Several well-known vehicle manufacturers are currently designing and testing systems that enable vehicles to drive high or fully automated.

What are the benefits of automated driving for society, regarding safety, traffic flow and environmental savings?

Furthermore, literature has provided insights in the benefits of automated driving for society. Main forecasted benefits are assigned to the increase of traffic safety, improved traffic flow, and more environmental savings. Traffic safety by automated driving is improved by prevention unsafe traffic participation, prevention of unsafe actions during driving and by reduction of the impact of accidents. Secondly, improved traffic flow is empowered as automated driving can allow closer headways between vehicles as the required reaction distance is much smaller than the distance needed for human reaction. Besides, communication with other vehicles and infrastructure can result in smooth braking and fine speed adjustments which will reduce destabilized traffic shockwave propagation. The third main benefit is the reduction of energy use. This is enabled by more efficient driving, lighter and more fuel-efficient vehicles and efficient infrastructure. This will reduce $C0_2$ emission and lower pollution. Although the actual effects depend on the exact actions of the system, the penetration rate and possible unintended side effects; some experts have made predictions of the level of benefits when collaborative systems take over control of primary driving tasks. Dutch experts in the field of automated systems, predict safety improvements of 25%, traffic flow improvements of 50%, and a reduction of pollution and CO_2 emission with respectively 20% and 10%. Dutch policy makers expect that fully automated driving is enabled around 2025. From this point on, effects of fully automated driving will be noticeable. Expectations on a global level are that between 2060 and 2080, society will highly benefit from fully automated driving opportunities.

How do the level of automation and driving circumstances determine the usage rate of automated driving systems?

The rate of usage depends highly on trust vehicle users have. Literature suggests that the experience of trust in driving situations depends on the interaction complexity between vehicle user, vehicle, and the driving environment. However, automated driving results in another role of the vehicle user. Therefore, interaction is changed which could result in changed preferences of interaction between vehicle user, vehicle, and driving environment. Besides characteristics of the vehicle users and the level of automation, identified driving circumstances within this interaction are the level of automation, weather and light circumstances, road type, length of the trip, density on the road, familiarity with the route and whether or not to perform a secondary task.

When automate driving is enabled in driving situations in which vehicle users experience enough trust to release control, usage of automated driving systems grows. Usage by the critical user mass is a requirement to achieve full benefit levels. Therefore, market planners should recognize that they should appeal the right value proposition to the right markets. For this, niches are important. They provide an environment for examining and adjusting learning processes such as technology, user preferences, regulations, and driving environment. Furthermore, niches offer stakeholders to create collaborations with other parties that support automated driving. Later on, widespread usage should be achieved.

What are the preferences concerning automated driving for different user groups?

Literature indicates that not all people are equally likely to embrace automated driving. However, different studies have indicated contradicting results concerning the willingness of males and females, and younger and older people to ride with automated vehicles. Results of the discrete choice experiment have pointed out that automated driving preferences of males and females, and younger and older vehicle users, do not differ that much. It seems that although all these user groups are not yet willing to release driving control, males and younger vehicle drivers are slightly less negative about ceding all driving tasks. Moreover, literature indicates that vehicle users with higher education are assumed to use automated driving systems more early than vehicle users with lower education. This is acknowledge by the results of the experiment. Further preferences are described below, when answering the main question. The main question reads:

Which level of automation and which driving circumstances contribute to the willingness of different vehicle user groups to release driving control?

An answer to this question is enabled by a discrete choice experiment. With data from this experiment, three types of choice models are described. The Mixed logit models give most useful insights in the preferences of different users groups and therefore the following conclusions are drawn from this model type.

The model for the overall sample indicates that the level of automation is most important for vehicle users' choice to release driving control. On average, vehicle users do not yet prefer full automation. Vehicle users seem neutral about high automation. Currently, only assisted driving or partial automation is preferred. However, there is high heterogeneity among the vehicle users concerning the level of automation. This indicates that within the sample, there could also be vehicle users that are already willing to cede all driving tasks. What the characteristics of these vehicle users are is not explained by their gender, age, level of education or experience with ITS.

Also the road type contributes to the willingness to release driving control. Vehicle users are most willing to cede driving tasks on highways, but vehicle users are on average also neutral to positive about releasing control on regional roads. Again, for this attribute much heterogeneity is observed. This heterogeneity is partly explained by the education level.

Familiarity with the route contributes, although in less extent than previous attributes, to the willingness of vehicle users to release driving control. Low heterogeneity is observed. This indicates that vehicle users do quite agree on the preference to release control on familiar routes. In addition, not performing a secondary tasks also contributes to the willingness to release control. Again for this attribute, low heterogeneity is observed which indicates that vehicle users do quite agree on this. These attributes thus show that vehicle users are not willing to release control when they are not familiar with the route and when have to perform a secondary task.

The length of the trip and the density on the road do not provide a compelling contribution to vehicle users' willingness to cede driving tasks.

These insights suggest that the level of complexity of the driving circumstances influence the willingness to release driving control. This supports previous research that vehicle users do not trust the technology's ability to perform better in safety-critical situations.

In short, it can be concluded that the following level of automations and driving circumstances contribute to the willingness of vehicle users to release control:

- Assisted driving or partial automation;
- Highways;
- Familiar route;
- Not performing a secondary task.

7.2 Managerial recommendations

Several stakeholders have high stakes concerning automated driving. Many vehicle manufacturers want to gain market share by designing a high or fully automated vehicle. Dutch policy makers are aiming to gain a global leadership role concerning knowledge about automated driving by implementing full automated driving on Dutch road network. Thereby, policy makers and other parties, such as transportation planners, regulators, and consumer supporting organizations want to decrease the number of accidents, improve the traffic flow and counteract climate change. For this, support from vehicle users is required. This is highly dependent on the control vehicle users want to release. The following guidelines are given to successfully implement automated driving.

7.2.1 Market planning

One requirement for market uptake of automated driving systems is that vehicle users trust the technology. To achieve the benefits of automated driving, public and private parties should work together in order to increase vehicle users' trust in automation. The automated systems should be known, understood and believed in, which requires education. However, one error of the technology could lead to immediate and widespread rejection of the technology. Therefore, it is crucial that vehicle users gain positive experience regarding automated driving. To increase trust, most important seems to be that vehicle users have understanding of the automated vehicle. This is important to highly important for half or the vehicle users. Additionally, the information of the effects and the extent of reliability research of the automated vehicle are important to vehicle users (respectively for 37 and 43%). Therefore, market planners should pay much attention to inform and educate vehicle users about automated driving.

Literature assumes that vehicle users with a high education level are to be the first to ride in vehicles with automated driving technology. This is also valid for vehicle users with much ITS experience. Although the choice models show that higher educated people and people with much ITS experience are not yet willing to use full automation, they are most willing to release control. Therefore, it is assumed that these user group will be the first to use full automation. They could form the niche users, which provide transport and market planners with more insights to stimulate widespread use of automated driving. Therefore, it is advised to first adjust the market plans to the preferences of this niche.

7.2.2 Transportation planning

Most support for automated driving can be found on highways. Therefore this road type offers most chance for successful and accepted implementation plans. For this reason it is advised to stakeholders to first focus on creating strong collaborations and feasibility studies for automated driving on highways. This could include elements such as road design, development of infrastructural support systems, regulations, and potentially achievable benefits. Eventually public parties should aim at also enabling automated driving on regional roads. On this road type, the highest safety benefit levels could be achieved.

Additionally, it is advised to enable automated driving on dense roads. Here the benefits for society are highest. On dense roads, many accidents happen and emissions are high. The density on the road does not have much influence on the willingness of vehicle users to release control, therefore it is assumed that vehicle users will use automated vehicles on within this driving circumstance.

Stakeholders should be careful with implementing partial, and especially high automated driving. During driving with these systems, it is expected from the vehicle user that he or she will take over control when necessary. Although vehicle users indicate that they prefer not to perform a secondary task while driving automated, many accidents have happened because drivers were distracted. In addition, vehicle users have indicated to prefer automated driving on familiar routes. However, people tend to pay less attention to the driving environment when they are familiar with the route. Hence, although highly automated technology should provide sufficient lead time to obtain the drivers attention when necessary, this is risky. Like in the current situation, small human errors could lead to fatal accidents.

Chapter 8

Discussion

In this chapter, this research findings are discussed. The results in the light of previous research are explained. Additionally, this chapter provides limitations of the research and opportunities for further research.

Not much research is done regarding vehicle users preferences of automated driving. As previously explained, literature disagrees on the gender and age levels of users that are often associated with the preference level for automated driving. Reason for this may be the different research methods. The models within this research indicate that there is not so much difference between these characteristics concerning their preferences. Also, previous research indicates that vehicle users use systems that take over the longitudinal task most on highways. Thereafter, it is most used on regional roads. These systems are least used on local roads. This is in accordance with the results of the experiment.

The first limitation of the research concerns the lack of insights in interaction effects upon choice. This is the combined effect on choice of two or more attributes, i.e. the effect multiple levels of different attributes could have upon each other. This insight could not be gained as the number of treatment combinations were reduced from 432 to 16, by fractional factorial design.

There are some limitations of this research concerning respondents sample. Only people that possess a passenger vehicle driver's license are taken in account for the experiment. This was due to the fact that for people who do not own a driving license it is very hard or impossible make a solid choice concerning their driving preferences. However, when fully automated driving is enabled on Dutch roads, it may also be possible that people without driving experience can use an automated vehicle. Their preferences could influence the results.

Additionally, this research aims at providing insights in the preferences of vehicle users concerning automated driving. Within the Mixed logit models, much heterogeneity was observed within the preferences. This heterogeneity could not be explained by further researching the preferences of vehicle users with differentiated gender, age, experience with ITS or education level. However, there can also be other user characteristics that could explain the heterogeneity. Rogers (2003) indicated that the preferences of different user groups could relate with users' social status and financial wealth. These characteristics are not incorporated in the research, as it is assumed that respondents are uneager to give information about these characteristics. However, they may be obtained with another approach. This could give valuable insights in what expected first adopters prefer.

Furthermore, with this research insights are gained in which situation users are willing to release control. However, for actual acceptation, also other elements are important. This includes elements such as costs, safety effects, liability, and privacy. Moreover, insights in more precise safety, traffic flow and environmental implications could lead to implementation plans that are more accurately adjusted to desired benefits. Future research should pay attention to the effects of automated driving in different driving situations. Much safety potential is attainted to automated driving, but in which driving situations this safety potential is achieved is not known yet. Transportation plans should be adapted to this. For example, it should be determined if automated driving should be enabled on normal city streets, or if automated driving is only enabled on dedicated automation lanes.

This thesis showed how vehicle-users perceived automated driving on different levels and with different driving circumstances. The proposed recommendations can be used as guidelines to work to a successful implementation of automated driving.

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Appendices

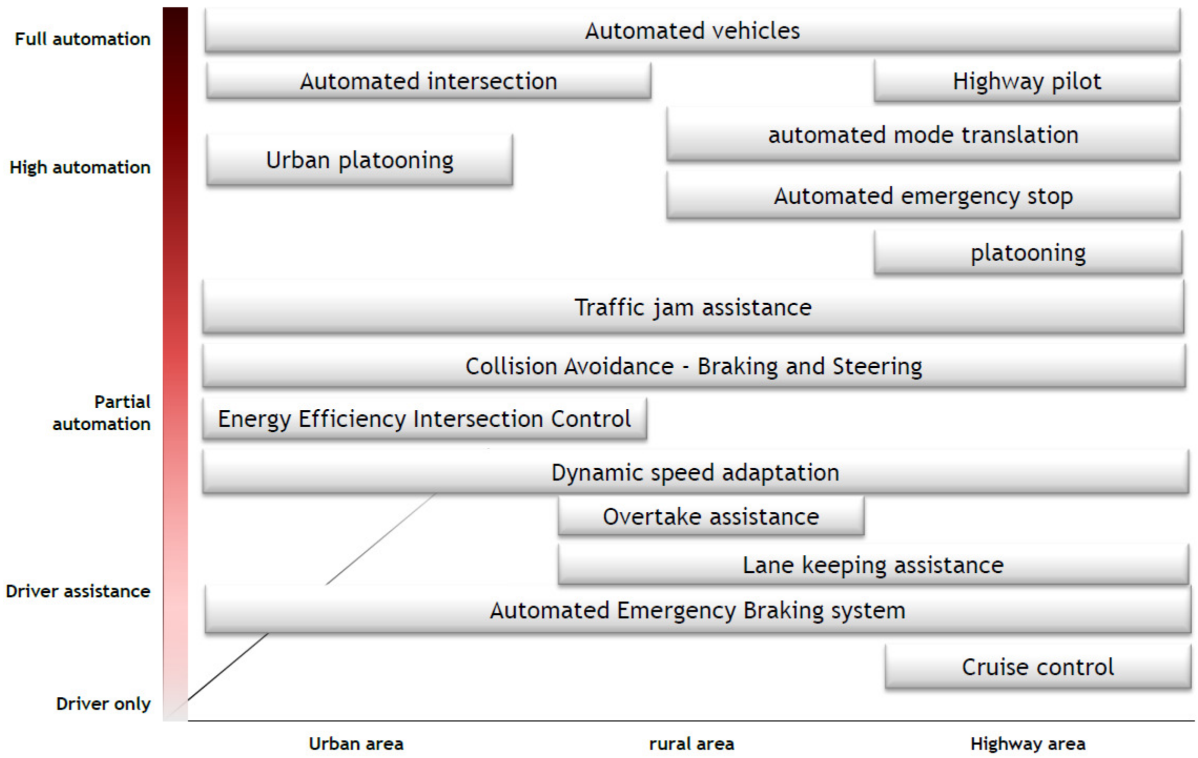
Appendix I Analogy between different categorizations of level of automation

Levels of automation

BASt expert group[1]	NHTSA[2]	SAE J3016[3]	Role of the driver	Examples
Driver only	Level 0 – No-Automation	Non-Automated	Full control	- (information and warning systems)
Assisted	Level 1 – Function-specific Automation	Assisted	Must permanently monitor. Resume control at any time.	CC, ACC, LKA, ESC
Partial automation	Level 2 - Combined Function Automation	Partial Automation	Must permanently monitor. Resume control at any time.	ACC and lane keeping, TJA
High automation	Level 3 - Limited Self-Driving Automation	Conditional Automation	Not required to monitor. Required to resume control after a certain lead time.	Lateral and longitudinal control automated
Full automation	Level 4 - Full Self-Driving Automation	High Automation	May be asked to but is not required to resume control.	Lateral and longitudinal control automated
-		Full Automation	Driverless vehicle	Lateral and longitudinal control automated

[1] T. M. Gasser, et al., "Legal consequences of an increase in vehicle automation (English translation),"Bundesanstalt für Straßenwesen (BASt), BASt-Report F83 (Part 1), 2013.
[2] National Highway Traffic Safety Administration, "Preliminary Statement of Policy Concerning Automated Vehicles." 2013.
[3] SAE International, "SAE J3016: Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems." 2014.

Appendix II Functional mapping of intelligent transport applications



Source: Working Group Automation in Road Transport, 2013. *Roadmap Automation in Road Transport,* iMobility Forum: iMobility Forum.

Appendix III Questionnaire

Technische Universiteit Eindhoven University of Technology

KenWiB

Kenniscluster energieneutraal wonen in Brainport

URBAN WHEELZ CENTER

Beste heer/mevrouw,

Graag nodig ik u uit om deel te nemen aan deze vragenlijst. De vragenlijst maakt een belangrijk deel uit van mijn afstudeeronderzoek aan de Technische Universiteit Eindhoven.

In deze vragenlijst worden vragen gesteld betreffende uw rijervaring en houding ten opzichte van de autonome (zelfrijdende) auto. Uw input wordt gebruikt om inzicht te krijgen in de bereidheid van automobilisten om controle aan de auto over te geven.

Het invullen duurt ongeveer 10 minuten. De vragenlijst bestaat uit vier delen met gesloten vragen. Uw antwoorden worden vertrouwelijk en anoniem verwerkt. Voor vragen of opmerkingen kunt u contact met mij opnemen via i.c.h.m.megens@student.tue.nl.

Alvast hartelijk dank voor uw medewerking,
Ilse Megens

Volgende

Bent u in het bezit van een autorijbewijs (rijbewijs B)?

- Ja
- Nee

Vorige Volgende

Deel 1: rijervaring en gedrag

In **het eerste deel** van de vragenlijst worden vragen gesteld over uw rijervaring en uw rijgedrag.

Hoeveel jaar rijervaring heeft u?

- Minder dan 5 jaar
- 5 - 19 jaar
- 20 - 34 jaar
- 35 - 49 jaar
- 50 jaar of meer
- Weet ik niet

Hoeveel kilometer reed u de afgelopen drie jaar gemiddeld per jaar in de auto?*

- Minder dan 10.000 kilometer
- 10.000 - 30.000 kilometer
- Meer dan 30.000 kilometer
- Weet ik niet

* Indien u minder dan drie jaar in het bezit bent van een rijbewijs, baseer uw antwoord dan op de jaren dat u wel in het bezit bent van een rijbewijs.

In wat voor soort auto rijdt u het meest?

- Een eigen auto
- Een leaseauto
- Een gratis ter beschikking gestelde auto
- Anders
- Ik rijd geen auto

In hoeverre bent u het eens met de volgende stelling?

Ik ga bewust om met brandstofgebruik om het milieu te sparen.

- Zeer oneens
- Oneens
- Neutraal
- Eens
- Zeer eens
- Weet niet / geen mening

Vorige | **Volgende**

Deel 1: rijervaring en gedrag

In hoeverre bent u het eens met de volgende stellingen?

	Zeer oneens	Oneens	Neutraal	Eens	Zeer eens	Weet niet / geen mening
Ik geniet van de spanning van gevaarlijk rijgedrag.						
Ik ben geneigd om voorzichtig te rijden.						
Ik verkijk me bij het inhalen op de snelheid van tegenliggers.						
Als ik in de file sta bedenk ik manieren om er sneller doorheen te komen.						

Vorige | **Volgende**

Deel 1: rijervaring en gedrag

In hoeverre bent u het eens met de volgende stellingen?

	Zeer oneens	Oneens	Neutraal	Eens	Zeer eens	Weet niet / geen mening
Ik ben nerveus tijdens het autorijden.						
Ik gebruik de claxon of flits met mijn lichten als een manier van frustratie-uiting.						
Op een kruispunt waar ik van rechts komend verkeer voorrang moet geven, wacht ik geduldig tot het kruisend verkeer gepasseerd is.						

Vorige | **Volgende**

Deel 1: rijervaring en gedrag

In hoeverre bent u het eens met de volgende stellingen?

	Zeer oneens	Oneens	Neutraal	Eens	Zeer eens	Weet niet / geen mening
Het geeft me plezier om op de snelheidsgrens te rijden.						
Ik reageer snel op onverwachte manoeuvres van andere bestuurders.						
Ik scheld naar andere bestuurders.						
Tijdens het rijden geldt voor mij 'beter het zekere voor het onzekere nemen'.						

Vorige | **Volgende**

Deel 1: rijervaring en gedrag

In hoeverre bent u het eens met de volgende stellingen?

	Zeer oneens	Oneens	Neutraal	Eens	Zeer eens	Weet niet / geen mening
Ik voel me bedrukt tijdens het autorijden.						
Ik vergeet wel eens dat mijn groot licht aan is totdat een andere bestuurder naar me flitst.						
Als ik in de file sta en auto's op de rijweg naast me beginnen te verplaatsen, probeer ik zo snel mogelijk daar tussen te voegen.						

Vorige | **Volgende**

Deel 2: intelligente systemen in de auto

In **het tweede deel** van de vragenlijst worden u vragen gesteld over intelligente systemen in de auto. Deze zijn volop in ontwikkeling en bedoelt om bereikbaarheid, comfort en/of veiligheid te verhogen. Hieronder worden enkele systemen genoemd.

Met welke van de volgende intelligente verkeerssystemen bent u bekend?

- [ ] Adaptive Distance Control
systeem houdt een bepaalde snelheid en afstand tot andere auto's en past deze automatisch aan wanneer nodig.

- [ ] Forward Collision Warning
systeem helpt om botsingen te voorkomen of de effecten te verminderen.

- [ ] Speed Regulation System
systeem past snelheid aan aan de toegestane maximale snelheid of ingegeven gewenste snelheid.

- [ ] Blind Spot Information System
systeem detecteert wanneer een ander voertuig zich in de dode hoek van de bestuurder bevindt.

- [ ] Lane Departure Warning / Lane Keeping Assist
systeem helpt de bestuurder om een goede positie op de rijweg te behouden.

- [ ] Navigatiesysteem
systeem biedt informatie over locatie en routebegeleiding.

- [ ] Fuel Efficiency Advisor
systeem biedt informatie over het verbruik van brandstof.

Vorige | **Volgende**

Deel 2: intelligente systemen in de auto

Van welke van de volgende intelligente verkeerssystemen heeft u ooit gebruik gemaakt?

- [ ] Adaptive Distance Control
systeem houdt een bepaalde snelheid en afstand tot andere auto's en past deze automatisch aan wanneer nodig.

- [ ] Forward Collision Warning
systeem helpt om botsingen te voorkomen of de effecten te verminderen.

- [ ] Speed Regulation System
systeem past snelheid aan aan de toegestane maximale snelheid of ingegeven gewenste snelheid.

- [ ] Blind Spot Information System
systeem detecteert wanneer een ander voertuig zich in de dode hoek van de bestuurder bevindt.

- [ ] Lane Departure Warning / Lane Keeping Assist
systeem helpt de bestuurder om een goede positie op de rijweg te behouden.

- [ ] Navigatiesysteem
systeem biedt informatie over locatie en routebegeleiding.

- [ ] Fuel Efficiency Advisor
systeem biedt informatie over het verbruik van brandstof.

Vorige | **Volgende**

Deel 2: intelligente systemen in de auto

De intelligente autosystemen kunnen ingedeeld worden aan de hand van hun functie.

- systemen die de bestuurder enkel **informeren**;
- systemen die de bestuurder **waarschuwen**;
- systemen die de rijtaken **overnemen**.

In de rest van deze vragenlijst ligt de focus op systemen die rijtaken **overnemen**.

In welke mate bent u bereid om bepaalde rijtaken over te laten nemen?

	Zeer lage mate	Lage mate	Gemiddelde mate	Hoge mate	Zeer hoge mate	Weet niet / geen mening
Snelheid-bepaling	○	○	○	○	○	○
Remmen en versnellen	○	○	○	○	○	○
Route-bepaling	○	○	○	○	○	○
Bepaling van positie op de weg	○	○	○	○	○	○

Vorige | **Volgende**

Deel 2: intelligente systemen in de auto

Als er samenwerkende systemen in de auto aanwezig zijn die de rijtaken **overnemen**, dan wordt deze auto ook wel (gedeeltelijk) autonoom genoemd.

Wat beïnvloedt uw bereidheid om gebruik te maken van de autonome auto?

	Zeer lage mate	Lage mate	Gemiddelde mate	Hoge mate	Zeer hoge mate	Weet niet / geen mening
Informatie over de effecten van de autonome auto.						
Het aantal toetsingen naar de betrouwbaarheid van de autonome auto.						
Mijn begrip van de autonome auto.						

Vorige Volgende

Deel 3: voorkeuren rijomstandigheden

Het derde deel betreft rijsituaties waarin u gebruik kunt maken van de autonome auto. Het doel is om inzicht te verkrijgen in de rijomstandigheden waarbij u gebruik zou maken van systemen die uw rijtaken overnemen.

De mate waarin systemen uw rijtaken kunnen overnemen wordt opgedeeld in vier niveaus.

- **Zeer weinig** rijtaken afstaan aan de auto. De gebruiker kan één hoofd-rijtaak afstaan. Hij of zij kan bijvoorbeeld de handen van het stuur óf de voeten van de pedalen houden. Gebruiker is geheel verantwoordelijk voor een veilige rit.

- **Weinig** rijtaken afstaan aan de auto. Op zijn minst twee samenwerkende hoofd-rijtaken kunnen worden afgestaan, bijvoorbeeld de handen van het stuur én de voeten van de pedalen houden. De gebruiker is verantwoordelijk voor een veilige rit en er wordt verwacht dat deze elk moment de rijtaken kan overnemen.

- **Veel** rijtaken afstaan aan de auto. In deze situatie kan de gebruiker alle hoofd-rijtaken onder bepaalde rijomstandigheden afstaan. Er wordt van de gebruiker verwacht dat deze actief kan reageren op incidentele gevallen waarin controle nodig is.

- **Alle** rijtaken afstaan aan de auto. Auto kan alle hoofd-rijtaken uitvoeren tijdens de gehele rit en de gebruiker hoeft de gehele rit niet op te letten.

De vijf andere categorieën rijomstandigheden die deel uitmaken van dit onderzoek zijn:

- Wegtype
- Lengte van de rit
- Verkeersdrukte op de weg
- Bekendheid met de route
- Het wel of niet uitvoeren van een bijkomende taak

Vorige Volgende

Deel 3: voorkeuren rijomstandigheden

Samengevoegd vormen de rijomstandigheden een specifieke rijsituatie. Een specifieke rijsituatie kan gevolgen hebben voor bijvoorbeeld de mate van sensatie, controle, inspanning of veiligheid die u ervaart.

Hieronder staat een voorbeeld met twee rijsituaties. Het is de bedoeling dat u uw rijsituatie van voorkeur geeft, dus in welke situatie u het liefst rijdt. Indien u in geen van de twee situaties bereid bent om te rijden, kiest u dan voor 'Geen van beide'.

Rijsituatie 1	Rijsituatie 2	Geen van beide
Veel rijtaken afstaan Lokale weg Rit van 20-100 km Hoge verkeersdrukte Bekend met de route Geen bijkomende taak*	Zeer weinig rijtaken afstaan Snelweg Rit van meer dan 100 km Lage verkeersdrukte Bekend met de route Wel een bijkomende taak*	
○	○	○

* bv. bellen of praten met een medepassagier

Op de volgende pagina's wordt u vier keer gevraagd om een dergelijke keuze te maken.

Vorige | **Volgende**

BLOCK 1

Deel 3: voorkeuren rijomstandigheden

Welke rijsituatie heeft uw voorkeur met betrekking tot de mate van rijtaken die u afstaat?

Rijsituatie 1	Rijsituatie 2	Geen van beide
Veel rijtaken afstaan Lokale weg Rit van minder dan 20 km Gemiddelde verkeersdrukte Onbekend met de route Wel een bijkomende taak*	Alle rijtaken afstaan Snelweg Rit van 20-100 km Gemiddelde verkeersdrukte Onbekend met de route Wel een bijkomende taak*	
○	○	○

* bv. bellen of praten met een medepassagier

Vorige | **Volgende**

Deel 3: voorkeuren rijomstandigheden

Welke rijsituatie heeft uw voorkeur met betrekking tot de mate van rijtaken die u afstaat?

Rijsituatie 1	Rijsituatie 2	Geen van beide
Zeer weinig rijtaken afstaan Regionale weg Rit van 20-100 km Gemiddelde verkeersdrukte Bekend met de route Geen bijkomende taak*	Veel rijtaken afstaan Snelweg Rit van meer dan 100 km Hoge verkeersdrukte Bekend met de route Geen bijkomende taak*	
◉	○	○

* bv. bellen of praten met een medepassagier

Vorige | **Volgende**

Deel 3: voorkeuren rijomstandigheden

Welke rijsituatie heeft uw voorkeur met betrekking tot de mate van rijtaken die u afstaat?

Rijsituatie 1	Rijsituatie 2	Geen van beide
Weinig rijtaken afstaan Regionale weg Rit van meer dan 100 km Lage verkeersdrukte Onbekend met de route Wel een bijkomende taak*	Veel rijtaken afstaan Regionale weg Rit van 20-100 km Gemiddelde verkeersdrukte Bekend met de route Wel een bijkomende taak*	
○	○	○

* bv. bellen of praten met een medepassagier

Vorige | **Volgende**

Deel 3: voorkeuren rijomstandigheden

Welke rijsituatie heeft uw voorkeur met betrekking tot de mate van rijtaken die u afstaat?

Rijsituatie 1	Rijsituatie 2	Geen van beide
Weinig rijtaken afstaan Snelweg Rit van 20-100 km Gemiddelde verkeersdrukte Onbekend met de route Geen bijkomende taak*	Weinig rijtaken afstaan Lokale weg Rit van 20-100 km Hoge verkeersdrukte Bekend met de route Wel een bijkomende taak*	
○	○	○

* bv. bellen of praten met een medepassagier

Vorige   Volgende

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BLOCK 2

Deel 3: voorkeuren rijomstandigheden

Welke rijsituatie heeft uw voorkeur met betrekking tot de mate van rijtaken die u afstaat?

Rijsituatie 1	Rijsituatie 2	Geen van beide
Zeer weinig rijtaken afstaan Regionale weg Rit van 20-100 km Hoge verkeersdrukte Onbekend met de route Wel een bijkomende taak*	Alle rijtaken afstaan Regionale weg Rit van minder dan 20 km Hoge verkeersdrukte Onbekend met de route Geen bijkomende taak*	
○	○	○

* bv. bellen of praten met een medepassagier

Vorige   Volgende

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Deel 3: voorkeuren rijomstandigheden

Welke rijsituatie heeft uw voorkeur met betrekking tot de mate van rijtaken die u afstaat?

Rijsituatie 1	Rijsituatie 2	Geen van beide
Zeer weinig rijtaken afstaan Snelweg Rit van minder dan 20 km Lage verkeersdrukte Bekend met de route Wel een bijkomende taak*	Veel rijtaken afstaan Regionale weg Rit van 20-100 km Lage verkeersdrukte Onbekend met de route Geen bijkomende taak*	
○	○	○

* bv. bellen of praten met een medepassagier

Vorige Volgende

Deel 3: voorkeuren rijomstandigheden

Welke rijsituatie heeft uw voorkeur met betrekking tot de mate van rijtaken die u afstaat?

Rijsituatie 1	Rijsituatie 2	Geen van beide
Alle rijtaken afstaan Regionale weg Rit van meer dan 100 km Gemiddelde verkeersdrukte Bekend met de route Wel een bijkomende taak*	Alle rijtaken afstaan Lokale weg Rit van 20-100 km Lage verkeersdrukte Bekend met de route Geen bijkomende taak*	
○	○	○

* bv. bellen of praten met een medepassagier

Vorige Volgende

Deel 3: voorkeuren rijomstandigheden

Welke rijsituatie heeft uw voorkeur met betrekking tot de mate van rijtaken die u afstaat?

Rijsituatie 1	Rijsituatie 2	Geen van beide
Zeer weinig rijtaken afstaan Lokale weg Rit van meer dan 100 km Gemiddelde verkeersdrukte Onbekend met de route Geen bijkomende taak*	Weinig rijtaken afstaan Regionale weg Rit van minder dan 20 km Gemiddelde verkeersdrukte Bekend met de route Geen bijkomende taak*	
○	○	○

* bv. bellen of praten met een medepassagier

Vorige | **Volgende**

Deel 4: persoonlijke kenmerken

Tot slot volgen er in **dit vierde deel** wat vragen over u als respondent.

Wat is uw geslacht?

- ○ Man
- ○ Vrouw

Wat is uw leeftijd?

- ○ Jonger dan 25 jaar
- ○ 25 - 39 jaar
- ○ 40 - 54 jaar
- ○ 55 jaar of ouder

Wat is uw hoogst genoten opleiding?

- ○ Geen, lager- of basisonderwijs
- ○ Voortgezet onderwijs
- ○ Middelbaar beroepsonderwijs
- ○ Hoger beroepsonderwijs of universiteit

Hoe is uw huishouden samengesteld?

- ○ Eenpersoonshuishouden
- ○ Meerpersoonshuishouden met kind(eren)
- ○ Meerpersoonshuishouden zonder kinderen
- ○ Anders

Vorige | **Volgende**

Deel 4: persoonlijke kenmerken

In welke stelling herkent u zich het meest?

- Ik houd vast aan tradities en materieel bezit.
- Ik zoek evenwicht tussen traditie en moderne waarden als consumeren en genieten.
- Ik streef naar een onbezorgd, plezierig en comfortabel leven.
- Ik ben gefascineerd door sociale status, nieuwe technologie, risico en spanning.
- Ik wil mezelf ontplooien, ben tegen sociaal onrecht en kom op voor het milieu.
- Ik leef in het hier en nu en doe niet mee met de morele en sociale gewoontes.
- Ik geef ruimte aan technologische ontwikkeling, maar verzet me tegen sociale en culturele vernieuwing.
- Ik hecht waarde aan ontplooien en beleven maar ook aan succes, materialisme en genieten.
- Ik weet niet / heb geen mening.

Vorige | **Volgende**

Opmerkingen

Heeft u naar aanleiding van deze vragenlijst nog opmerkingen en/of suggesties?

Vorige | **Volgende**

Dit is het einde van de vragenlijst.

Hartelijk dank voor uw deelname aan dit onderzoek.

Met vriendelijke groet,
Ilse Megens

Appendix IV Link between level of familiarity with ITS, and gender and age

	Young male	Young female	Old male	Old female
Low familiarity	86	137	86	122
Expected	112,07	113,35	105,67	99,90
Chi square	6,07	4,93	3,66	4,89
High familiarity	89	40	79	34
Expected	62,93	63,65	59,33	56,10
Chi square	10,80	8,79	6,52	8,70

The chi-square is 54,357, with a p-value of less than 0,001.

Appendix V Willingness to release control of driving tasks to automated systems

User group	Prefer AD	Expected	Prefer no AD	Expected	Chi-square	Significant at p < 0,05
Gender						
Male	320	309,69	20	30,31		
Female	293	303,31	40	29,69		
					7,784	*
Age						
18-24	109	104,75	6	10,25		
25-39	222	215,87	15	21,13		
40-55	157	154,84	13	15,16		
55+	125	137,54	26	13,46		
					17,045	*
Education						
Primary education	2	3,64	2	0,36[1]		
Secondary education	66	71,05	12	6,95		
Lower education (MBO)	202	208,58	27	20,42		
Higher education/university	343	329,73	19	32,27		
					20,659	*
Household situation						
Single person household	114	112,57	10	11,43		
Multiple person household with children	249	243,29	19	24,71		
Multiple person household without children	218	225,14	30	22,86		
					4,104	
Driving experience						
Less than 5 year	102	97,45	5	9,55		
5-19 year	251	245,89	19	24,11		
20-34 year	152	150,27	13	14,73		
35 or more year	107	118,39	23	11,61		
					16,074	*
Kilometers per year						
Less than 10.000	223	227,14	25	20,86		
10.000-30.000	290	289,43	26	26,57		
More than 30.000	86	82,43	4	7,57		
					2,750	
ITS familiarity						
Low	378	392,58	53	38,420		
High	235	220,42	7	21,580		
					16,880	*
ITS experience						
Low	386	398,04	51	38,960		
High	227	214,96	9	21,040		
					11,649	*
Trust						
Low	94	104,61	19	8,390		
Average	292	291,61	23	23,389		
High	200	189,78	5	15,221		

Continuation of Table

User group	Prefer AD	Expected	Prefer no AD	Expected	Chi-square	Significant at p < 0,05
<u>Personality traits</u>						
Self-esteem						
High	113	112,03	10	10,966		
Low	500	500,97	50	49,034		
					0,114	
Need for control						
High	120	112,95	4	11,055		
Low	493	500,05	56	48,945		
					6,059	*
Sensation seeking						
High	119	121,14	14	11,857		
Low	494	491,86	46	48,143		
					0,530	
Extraversion						
High	216	223,16	29	21,842		
Low	397	389,84	31	38,158		
					4,049	*

[1] Chi-square condition is violated: expected value is below 1 (Cochran, 1954)

Appendix VI Correlation matrix of estimated attribute-levels

	Very little Tasks	Little tasks	Many tasks	Local road	Reg. road	<20 km	20-100 km	Low density	Average. density	Familiar w. road	Second. task
Very little tasks	1,00000	0,50250	0,50166	0,00334	0,00327	0,00000	-0,00234	-0,00335	0,00048	-0,00235	-0,00709
Little tasks	0,50250	1,00000	0,50250	0,00001	0,00374	0,00667	-0,00188	-0,00335	-0,00185	0,00001	-0,00474
Many tasks	0,50166	0,50250	1,00000	0,00000	-0,00234	0,00333	-0,00514	-0,00670	-0,00513	-0,00235	-0,00237
Local road	0,00334	0,00001	0,00000	1,00000	0,41925	0,00334	-0,00046	0,00670	0,00513	-0,00237	-0,00235
Regional road	0,00327	0,00374	-0,00234	0,41925	1,00000	0,00327	0,02941	0,00282	0,03456	-0,00531	-0,00133
<20 km	0,00000	0,00667	0,00333	0,00334	0,00327	1,00000	0,42232	0,00335	0,00328	-0,00235	0,00235
20-100 km	-0,00234	-0,00188	-0,00514	-0,00046	0,02941	0,42232	1,00000	0,00563	0,03019	-0,00065	0,00065
Low density	-0,00335	-0,00335	-0,00670	0,00670	0,00282	0,00335	0,00563	1,00000	0,41868	0,00000	0,00000
Average density	0,00048	-0,00185	-0,00513	0,00513	0,03456	0,00328	0,03019	0,41868	1,00000	-0,00266	0,00266
Familiar w. route	-0,00235	0,00001	-0,00235	-0,00237	-0,00531	-0,00235	-0,00065	0,00000	-0,00266	1,00000	-0,00668
Second. task	-0,00709	-0,00474	-0,00237	-0,00235	-0,00133	0,00235	0,00065	0,00000	0,00266	-0,00668	1,00000

Appendix VII Multinomial logit model

Attribute	β_k	P < 0,05
Constant	0,48607	*
Level of released driving tasks		
Release very little tasks	0,39681	*
Release little tasks	0,23854	*
Release many tasks	-0,07387	
Release all tasks	-0,56148	
Road type		
Local road	-0,31523	*
Regional road	0,10516	*
Highway	0,21007	
Length of trip		
<20 km	0,03304	
20-100 km	0,03917	
>100 km	-0,07221	
Density on road		
Low	0,03819	
Average	-0,05752	
High	0,01933	
Familiarity with route		
Familiar	0,02025	
Unfamiliar	-0,02025	
Secondary task		
Yes	-0,11466	*
No	0,11466	
LL_M	-2806,770	
LL_0	-2957,464	
R^2	0,051	
D	301,389	

Appendix VIII Latent class model

		Class 1		Class 2	
		β_k	P < 0,05	β_k	P < 0,05
Constant		-2,06937	*	2,11394	*
Level of released driving tasks					
	Release very little tasks	1,48349	*	0,20433	*
	Release little tasks	0,43872	*	0,16769	
	Release many tasks	-0,01479		0,05413	
	Release all tasks	-1,90742		-0,42615	
Road type					
	Local road	-0,01355		-0,38263	*
	Regional road	-0,02162		0,10761	
	Highway	0,03517		0,27502	
Length of trip					
	<20 km	0,33395	*	0,06856	
	20-100 km	-0,09960		0,07609	
	>100 km	-0,23435		-0,14465	
Density on road					
	Low	-0,06967		0,14916	
	Average	0,22007		-0,14605	
	High	-0,15040		-0,00311	
Familiarity with route					
	Familiar	0,15579		-0,04116	
	Unfamiliar	-0,15579		0,04116	
Secondary task					
	Yes	-0,51502	*	0,01954	
	No	0,51502		-0,01954	
		θc		θc	
Constant		0		0,97894	*
Gender		0		0,31131	*
Age		0		-0,24181	*

Appendix IX   Mixed logit model for overall sample

		Mean	P < 0,05	Sig. st. dev.
Constant		2,06009	*	3,78225
Level of released driving tasks				
	Release very little tasks	0,70429	*	1,46979
	Release little tasks	0,59185	*	1,12151
	Release many tasks	-0,00044	*	0,48443
	Release all tasks	-1,29570		
Road type				
	Local road	-0,53173	*	0,62873
	Regional road	0,15712	*	
	Highway	0,37461		
Length of trip				
	<20 km	-0,17319		0,74229
	20-100 km	0,13135	*	
	>100 km	0,04184		
Density on road				
	Low	0,13807		
	Average	-0,09713		
	High	-0,04094		
Familiarity with route				
	Familiar	0,21759	*	
	Unfamiliar	-0,21759		
Secondary task				
	Yes	-0,21778	*	
	No	0,21778		
LL_M		-2455,546		
LL_0		-2957,464		
ajd. R^2		0,164		

Appendix X Mixed logit models for males and females between 18 and 39 years old

	Male, 18-39			***Female, 18-39***		
	Mean	**P < 0,05**	**Sig. st. dev.**	**Mean**	**P < 0,05**	**Sig. St. dev.**
Constant	3,26002	*	3,33767	1,67312	*	3,57065
Level of released driving tasks						
Release very little tasks	0,41901		1,35176	0,90532	*	1,37209
Release little tasks	0,66220	*	1,05992	0,66845	*	1,25007
Release many tasks	-0,10211			0,03965		
Release all tasks	-0,97910			-1,61342		
Road type						
Local road	-0,37251	*	0,61274	-0,61759	*	
Regional road	0,10663			0,28938	*	
Highway	0,26588			0,32821		
Length of trip						
<20 km	-0,07314			-0,28076		
20-100 km	0,10204		0,63831	0,20390		0,53041
>100 km	-0,02890			0,07686		
Density on road						
Low	-0,29214			0,51221	*	
Average	0,09381			-0,24598		
High	0,19833			-0,26623		
Familiarity with route						
Familiar	0,15566		0,47547	0,26919	*	
Unfamiliar	-0,15566			-0,26919		
Secondary task						
Yes	-0,30447	*		-0,20195	*	
No	0,30447			0,20195		
LL_M	-626,882			-633,585		
LL_0	-769,029			-777,818		
ajd. R^2	0,161			0,165		

Appendix XI Mixed logit models for males and females of 40 year or older

	Male, 40+			*Female, 40+*		
	Mean	**P < 0,05**	**Sig. st. dev.**	**Mean**	**P < 0,05**	**St. dev.**
Constant	1,86616	*	3,48762	1,01351	*	3,57065
Level of released driving tasks						
Release very little tasks	0,59946	*	1,71602	0,93148	*	
Release little tasks	0,20410			0,50725	*	
Release many tasks	0,06317			-0,18843		
Release all tasks	-0,86673			-1,25030		
Road type						
Local road	-0,50133	*	0,77471	-0,45350	*	0,82896
Regional road	0,14714			0,05998		
Highway	0,35419			0,39352		
Length of trip						
<20 km	-0,18143		0,92204	0,18886		
20-100 km	0,17720			-0,17085		
>100 km	0,00423			-0,01801		
Density on road						
Low	0,14608			-0,15834		
Average	-0,24778			0,09333		
High	0,10170			0,06501		
Familiarity with route						
Familiar	0,13733			0,11317		
Unfamiliar	-0,13733			-0,11317		
Secondary task						
Yes	-0,12707	*		-0,44077	*	
No	0,12707			0,44077		
LL_M	-610,086			-554,475		
LL_0	-725,084			-685,534		
ajd. R^2	0,137			0,171		

Appendix XII Mixed logit models for ITS experience

	Much			*Little*		
	Mean	**p < 0,05**	**Sig. St. dev.**	**Mean**	**p < 0,05**	**St. dev.**
Constant	3,20559	*	3,91238	1,56576	*	3,65657
Level of released driving tasks						
Release very little tasks	0,95023	*	1,89093	0,60795	*	1,22810
Release little tasks	0,68683	*	2,09099	0,47027	*	
Release many tasks	-0,15759			0,05451		
Release all tasks	-1,47947			-1,13273		
Road type						
Local road	-0,97142	*	0,88129	-0,39845	*	0,57892
Regional road	0,29871			0,13185		
Highway	0,67271			0,26660		
Length of trip						
<20 km	-0,36844		0,86310	0,00887		0,57197
20-100 km	0,16302		0,63634	0,09722		
>100 km	0,20542			-0,10609		
Density on road						
Low	0,09950			0,16420		
Average	-0,31712			-0,04399		
High	0,21762			-0,12021		
Familiarity with route						
Familiar	0,36873	*	0,75831	0,09986		
Unfamiliar	-0,36873			-0,09986		
Secondary task						
Yes	-0,29061	*		-0,19485	*	
No	0,29061			0,19485		
LL_M	-835,226			-1598,140		
LL_0	-1037,090			-1920,374		
ajd. R^2	0,176			0,159		

Appendix XIII Mixed logit models for education level

	Basic			**Lower**			**Higher**		
	Mean	**p<0,05**	**Sig. st. dev.**	**Mean**	**P<0,05**	**Sig. st. dev.**	**Mean**	**p<0,05**	**Sig. st. dev.**
Constant	0,59093	*	3,56747	1,71961	*	3,73352	2,54041	*	3,46363
Level of released driving tasks									
Release very little tasks	0,78758	*		0,63433	*	1,05750	0,68601	*	1,81436
Release little tasks	0,10316	*	1,26888	0,56615	*	0,82881	0,72869	*	1,28236
Release many tasks	0,00979			0,06940			-0,11385		
Release all tasks	-0,90053			-1,26988			-1,30085		
Road type									
Local road	-0,58114	*	0,82595	-0,31022	*		-0,59518	*	
Regional road	-0,01474			0,05292			0,23170	*	
Highway	0,59588			0,25730			0,36348		
Length of trip									
<20 km	-0,00076			-0,10164			-0,19696		0,90051
20-100 km	-0,05172			0,03594			0,27025	*	0,61384
>100 km	0,05248			0,06570			-0,07329		
Density on road									
Low	0,23845			0,20923			-0,08230		
Average	-0,00882			-0,14898			-0,08986		
High	-0,22963			-0,06025			0,17216		
Familiarity with route									
Familiar	0,17191	*	0,54037	0,16310			0,19734	*	
Unfamiliar	-0,17191			-0,16310			-0,19734		
Secondary task									
Yes	-0,32847	*		-0,14217			-0,21130	*	
No	0,32847			0,14217			0,21130		
LL_M	-301,863			-832,659			-1294,060		
LL_0	-360,345			-1006,329			-1590,791		
ajd. R^2	0,118			0,158			0,176		

VEHICLE USERS' PREFERENCES CONCERNING AUTOMATED DRIVING
Implications for transportation and market planning

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ABSTRACT
Automated driving could highly benefit society by improved safety, traffic flow and increased environmental savings. To enable this, vehicle users should release their driving control to automated driving systems. However, it is not granted that vehicle users are willing to release control in all driving circumstances. Results from a discrete choice experiment show that vehicle users willingness to release control is highly dependent of the level of automation, as users strongly only prefer a low level of automation. Furthermore, vehicle users only want to release control on highways, on roads they are familiar with and only when they do not perform a secondary task.

Keywords: automated driving, passenger vehicle mobility, driving circumstances, stated choice, discrete choice models.

INTRODUCTION
Passenger vehicle mobility provides economical and personal growth by enabling daily activities. However, mobility also exposes society to some dangers. These are the results of the everlasting demand for mobility. This leads to three key societal challenges.

Societal challenges concerning passenger vehicle mobility
Firstly, every year, accidents cost Dutch society around 12,5 billion euro. Motorized vehicles have a high share in this. They are involved in half of the traffic accidents. These accidents mainly occur due to human errors. Secondly, the distance vehicle users travel, as well as the amount of vehicles on the road is expanded. This results in increased congestion and delayed traffic flow. Total congestions costs were between 1,8 and 2,4 billion euro in 2009. More than two-third of these costs are on account of passenger driving. Thirdly, vehicles emit greenhouse gasses, which have negative influence on people's health and cause damages to the environment. One-fifth of the total CO_2 emissions in the Netherlands is caused by traffic, of which more than half is due to passenger vehicles. In total, the costs of emissions and pollution by traffic were around 5,1 billion euro in 2012 (Kennisinstituut voor Mobiliteitsbeleid, 2013).

Technological solution
One of the solutions for the above mentioned challenges are Intelligent Transportation Systems (ITS). These benefits have been recognized by different Dutch platforms. ITS systems are based on information and communication technologies and enable a flexible and dynamic traffic system. A successive step different stakeholders are working on to further aid society is the implementation of automated driving. An automated driving experience is enabled by systems that take over driving control from humans. The introduction of automated driving results in a new role division between the vehicle user, the vehicle and the driving environment. Within this new role division, vehicle users have to release control. However, literature indicates that vehicle users are not always eager to do this. They seem to trust themselves more in correctly carrying out control than they trust automated systems in doing this. Therefore, no matter how intelligent the technology may be, not trusting the system may be rejected. Hence, the vehicle user's willingness to release control regarding the level of automation and the driving circumstances, determine the benefits levels of automated driving for society (Muir, 1987; Secretary Schultz van Haegen, 2014; SWOV, 2010).

Research questions
Literature lacks insights in the preferences concerning automated driving. Therefore this research aims to answer the following main question:

> **Which level of automation and which driving circumstances contribute to the willingness of different vehicle user groups to release driving control?**

To support the main question, four sub-questions are defined:
- What is automated driving and what are current and expected technological capabilities?
- What are the benefits of automated driving for society, regarding safety, traffic flow and environmental savings?
- How do the level of automation and driving circumstances determine usage rate of automated driving systems?
- What are the preferences concerning automated driving for different user groups?

Besides theoretical insights in the preferences of vehicle users, answering these questions offers insights which provide managerial guidelines for successful implementation of automated driving. Transportation and market planners can take measures that are in accordance with preferences of vehicle-users and hence maximize the potential benefits of automated driving.

This research provides insights concerning automated passenger driving. It does not involve freight traffic or automated parking. Furthermore, it only explains how automated driving could benefit society, and does not pay attention to the benefits for individuals. In addition, it does not describe how individual motives such as costs, liability and privacy have influence on the willingness to use automated systems. The research focuses on the Netherlands as the Dutch road network copes with very dense traffic conditions and automated driving can have high benefit levels. Additionally, Dutch government is aiming at a leading role in implementation of automated driving and therefore will stimulate the use of automated driving systems (Secretary Schultz van Haegen, 2014).

Outline

The thesis will firstly provide answers to the first three sub-questions by obtaining knowledge from literature. Next, a discrete choice experiment aims to answer the main question and the last sub-question. Therefore, first theory on discrete choices is described, after which the design of the experiment is explained. From the experiment, preferences of vehicle users are identified, which leads to conclusions and recommendations for stakeholders. The thesis is finalized with a discussion of the results .

AUTOMATED DRIVING

In recent years, vehicle manufacturers seem to have developed a technologies that can enable people to travel without being constantly attentive. The development of these kinds of technology started with systems that could sense and react with an appropriate movement. Later on, technological developments accelerated and then also the outside driving environment could be managed. Between 2003 and 2008, several automated driving challenges were embraced that resulted in vehicles that could drive with automated systems in a mock city environment. Currently, many well-known vehicle manufacturers are working on fully automated vehicles and have started test drives on real roads (Anderson, et al., 2014).

Technological developments

Technologies behind automated driving depend on three factors. Firstly, in-car systems provide information. Secondly, applications that allow communications between other vehicles and with infrastructure. Thirdly, autonomous systems that independently respond to situations, by sensors, scanners, etc. Therefore, the term 'automated' refers to vehicle being operated by a machine, by using communication as well as own sensors (Timmer, et al., 2013). Automated control can be split up to different levels. BASt expert group has categorized these levels as shown in Table 1. Currently only assisted driving and partial automation are available to public.

Table 1. Concise description of levels of automation (Gasser, et al., 2013)

Levels of automation	Role-divsion of driver and system
Driver only	The driver continuously (throughout the complete trip) accomplishes longitudinal (accelerating/ braking) and lateral (steering) control.
Assisted	The driver continuously accomplishes either lateral or longitudinal control. The other/remaining task is – within certain limits - performed by the system.
Partial automation	The system takes over the lateral and longitudinal control (for a certain period of time and/or in specific situations).
High automation	The system takes over lateral and longitudinal control for a certain period of time in specific situations.
Full automation	The system takes over lateral and longitudinal control completely within the specification of the application.

Implications for society

Main benefits of automated driving are increased traffic safety, improvement of traffic flow, and increased environmental savings. Traffic safety can be improved as automated systems can detect and neutralize safety-critical events more adequately than human drivers. The systems prevent unsafe traffic participation, unsafe actions during traffic participation, and reduce the impact of accidents (SWOV, 2010). The number of road fatalities could decline with 25% when ITS work together (Arem, et al., 2008). However, as 90% of the accidents occur due to human errors, some experts predict that the safety benefits could eventually be higher. The second main benefit concerns an improved traffic flow. Automation in following vehicles can communicate and therefore respond on each other by smooth braking and fine speed adjustments. This leads to reductions in destabilized traffic shockwave propagation. Additionally, automation enables existing roads to be more efficiently used. Collaborating ITS could reduce congestion with 50% (Arem, et al., 2008). The third main benefit is the reduction of energy use and emissions. Energy use can be decreased by more efficient driving, lighter and more fuel-efficient vehicles and efficient infrastructure. CO_2 is reduced by an improved composition of the fleet and less influence of negative human driving behavior. This could result in 20% less pollution and 10% less CO_2 when ITS work together (Arem, et al., 2008).

Future planning and challenges

A roadmap concerning automated driving implementation is set up by Secretary Schultz van Haegen (2014). The Secretary's aim at testing highly automated driving between 2015 and 2020. Around 2025, highly and fully automated driving is assumed to be enabled. Litman (2014) predicts that between 2040 and 2060 the level of the exact benefits are tangible. Additionally, between 2060 and 2080 most vehicles will be fully automated and society will highly profit from the benefits. However, still many issues need to be addressed before this can become reality.

INFLUENCING USAGE RATE OF AUTOMATED DRIVING SYSTEMS

Vehicle user, vehicle, driving environment

Driving is a cohesion between the user, the vehicle, and the driving environment, which is depicted in Figure 1. For a large extent, these elements determine the task requirements for vehicle users. Automated driving changes the role of the vehicle user within this interaction framework. Under high influence of trust in automation, the preferred interaction with the vehicle and driving environment is determined.

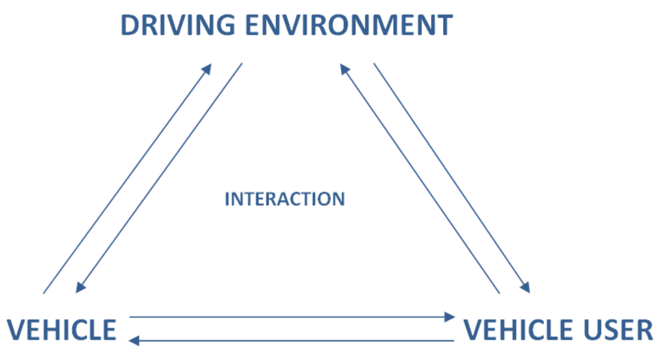


Figure 1: Traffic interaction framework

There is a strong relationship between trust and automated systems. Driving does not allow a margin of error as vehicles pass humans on little distance. Therefore indicates that people will only release driving control when they experience sufficient trust in the driving circumstances (Muir, 1987). Seven different attributes are identified from literature which have influence on how vehicle users experience driving. These are shortly explained below.

Weather and light circumstances - Driving risks increase when it is dark, rainy, snowy or foggy. Vehicle users will adapt their driving behavior to this (Mesken, 2012).
Road type - The uniformity of the road type influence vehicle users perception of safety. Therefore, the task requirement is higher when driving in urban areas, than on regional roads, or even more higher when driving on highways (Mesken, 2012).
Density of traffic on the road - The higher the density on the road, the more task requirements vehicle users experience. However, also the more advanced the automated driving systems should be (Mesken, 2012).
Length of the trip - During long distance driving, vehicle users have to be concentrated for a longer time, therefore they experience long trips different than short trips (Sanchez, et al, 2012).
Familiarity with the route - Vehicle users pay less attention to the driving environment when they are familiar with the route. The difficulty level of driving which is experienced decreases when familiarity increases (Yanko & Spalek, 2013).
Secondary task - Besides maintaining safety while driving, vehicle users are also often involved in more comfort related tasks, such as making phone calls or talking to a fellow passenger.

Implementing automated driving in line with users' preferences
Achievement of potential benefit levels depends on whether or not a critical user mass is willing to release control. Therefore, the use of automated driving systems should spread among vehicle users. This usage is expected to gradually happen over an S-curved line, and is explained as a diffusion process. The uptake by vehicle users can be divided in different user categories. First a certain niche will use automated driving systems. Within this niche, often people with high education, high social status, and high financial means are found. This niche will provide stakeholders with knowledge to improve transportation and market plans. Identified stakeholders that have influence on transport and/or market plans are policy makers, regulators, transportation planners, consumer supporting organizations, vehicle manufacturers, and vehicle users.

Choice process
Insights in which driving situation vehicle users would choose to release control, can be obtained by discrete choice modeling. A discrete choice model can describe the decision process of a vehicle user in a particular driving situation. Compared to more traditional approaches, an advantage of a choice-approach is that individuals will less overestimate the importance of unimportant attributes, as well as underestimate the important attributes (Hensher, et al., 2005). For this research, the driving situation is determined by the level of automation and different driving circumstances. The level of automation and the driving circumstances are referred to as the attributes, the individual is represented by the vehicle user, and a driving situation is the alternative context.

MEASURING DISCRETE CHOICES
According to the random utility theory, individuals will base the preferred choice amongst alternatives, on the alternative with the highest utility. The utility of an alternative, and part-worth utilities per attribute can be derived with discrete choice models. The Multinomial logit (MNL) model is the most basic and widely used model. It has a short estimation time, computation is simple, and it is easy to measure how well it predicts the data. Additionally, it

gives one set of globally optimal parameters and is therefore easy to interpret. However, the MNL model is homogeneous of degree zero in attributes. Therefore it could be useful to (also) model the data with a Latent class (LC) model. Compared to the MNL model, heterogeneity can be observed by discrete parameter variation. Respondents who have similar observed variable distributions are implicitly grouped into the same latent class with parameters to be estimated. The drawbacks of this model are that it is not known by the researcher which particular individual contains which class, Additionally, an extra analysis is needed to decide the number of classes (Greene & Hensher, 2003). A more adequate model than the LC model is the Mixed logit model. This model is more useful in terms of its overall flexibility and range of choice behavior it can accommodate. It can explain individual differences in the mean of the attribute levels (Greene & Hensher, 2003). It differs with MNL as Mixed logit does also not require to make specific assumptions about the distribution of parameters across individuals. The disadvantage is that the application of this model is not easy. Estimating the parameters is time consuming and parameters are difficult to interpret (Hensher, et al., 2005).

EXPERIMENT DESIGN

To obtain data for the choice models, a discrete choice experiment is done by the distribution of an online survey throughout Dutch speaking people that possess a passenger drivers license. The experiment construction is based on guidelines of Hensher, et al. (2005). The survey consists of four parts. The first part aims to get insights in the respondent's driving experience and personality traits regarding driving. Next, the following part pays attention to the respondent's view on Intelligent Transportation Systems. It will invite respondents to give importation about their familiarity and experience with ITS, and measures how important three trust aspects are to respondent. The third part uses stated choice response to find the automated driving preferences of respondents. Stated choice data derives choices that are made in given hypothetical situations (Hensher, et al., 2005). It allows robust understanding of how individuals make choices by observing multiple choices from individuals. Within these hypothetical situations, six attributes with associated levels are presented to the respondent. The six attributes with associated levels can be found in Table 2. For only the experiment, the level of automation correspondents with the level of released driving tasks, as this label is more easy to interpret for respondents. The respondents are asked to choose the situation that have their preference. In the last part, socio-demographic and psychographic factors are asked. Socio-demographic factors include gender, age, education level and household situation. Insights in psychographic factors are based on a division of lifestyles, to which consumption behavior is often closely linked.

Table 2. Selected attributes and corresponding levels

Attribute	Level			
Level of released driving tasks	Very little tasks	Little tasks	Many tasks	All tasks
Road type	Local road	Regional road	Highway	
Length of trip	<20 km	20-100 km	>100 km	
Density on road	Low	Average	High	
Familiarity with route	Familiar	Unfamiliar		
Secondary task	Yes	No		

IDENTIFYING VEHICLE USERS' PREFERENCES

Description respondents

With the survey, data from 673 respondents is collected. A concise description of the respondents can be seen in Table 3.

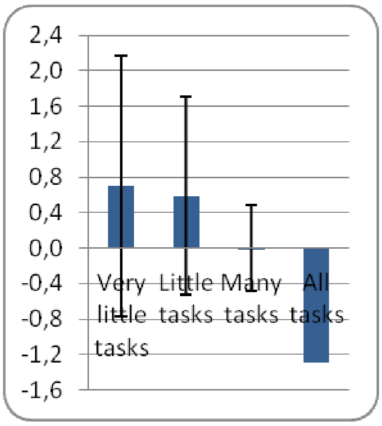
Table 3. Characteristics of the sample

User group	Research sample
Gender	
Male	51%
Female	49%
Age[1]	
18-24	17%
25-39	35%
40-54	47%
55 +	
Education	
Primary education	1%
Secondary education	12%
Lower education (MBO)	34%
Higher education/university	54%

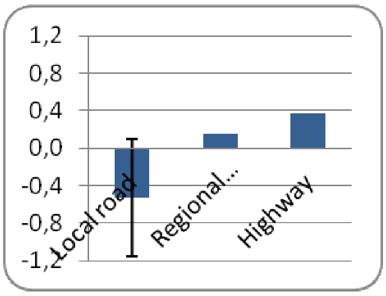
[1] The total sample of the different characteristics is not always 100%. This is caused by rounding-off.

From further descriptive analyses it appears that several user characteristics are found to explain possible differences in the willingness to release control of driving tasks. These characteristics are gender, age, education, driving experience, familiarity and experience with ITS, trust and two personality traits. Because of time constraints, only gender, age, education level and experience with ITS are taken in account for the model analysis. The Multinomial logit model appears to have a very weak model fit. Therefore, this model will not be further examined. The results of the Latent class model show to have a better fit. The Latent class model includes two classes that take in account gender and age. This results in one class that is negative about automated driving, and a second class that is positive about automated driving. The level of released tasks and whether or not to perform a secondary task are very important to the first class. The second class emphasizes the importance of level of released control and road type.

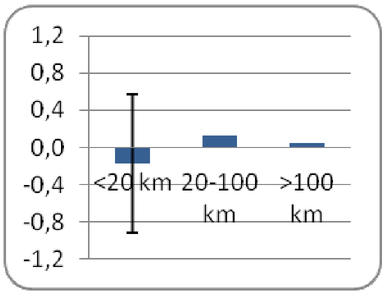
To get more insights in taste heterogeneity with different user groups, Mixed logit is applied. Mixed logit models are described for the total sample and for respondents with different gender, age, ITS experience and education level. The means of all attribute-levels of the model for the total sample are shown in Figures 2a-f. The means of other described model quite overlap with the presented model. The figures show that the level of released driving tasks, road type, familiarity with the route and whether or not to perform a secondary task contribute to vehicle users willingness to release control to automated systems. The Mixed logit models are further described in the conclusions.



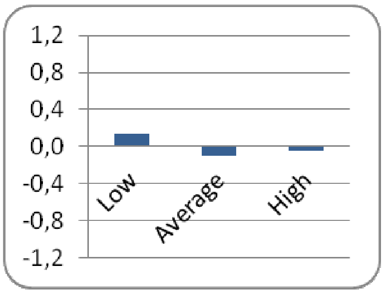
a. Level of released driving tasks



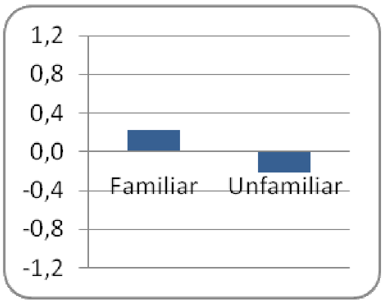
b. Road type



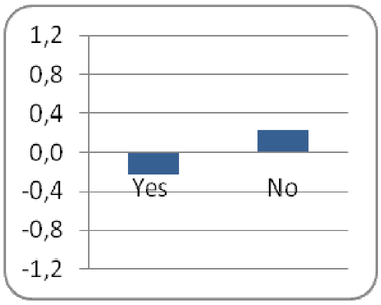
c. Length of trip



d. Density on road



e. Familiarity with route



f. Secondary task

Figures 2a-f: Means of the attribute-levels

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

With a discrete choice experiment, insights have been gained concerning which level of automation and which driving circumstances contribute to the willingness of vehicle users to release driving control. Vehicle users' choice process is eventually described by two choice models: Latent class model and Mixed logit model. The Mixed logit model gives most useful insights in the preferences of different users groups and therefore the following conclusions are drawn from this model. The model for the overall sample indicates that the level of automation is most important for vehicle users' choice to release driving control. On average, vehicle users do not yet prefer full automation, only assisted driving or partial automation is preferred. High heterogeneity is observed which indicates that there could also be users that are already willing to release full control. What the characteristics of these vehicle users are that are willing to release full control is not explained by their gender, age, level of education or experience with ITS. Furthermore, also the road type contributes to the willingness to release driving control. Vehicle users are most willing to cede driving tasks on highways, but vehicle users are on average also neutral to positive about releasing control on regional roads. Again, for this attribute much heterogeneity is observed. This heterogeneity is partly explained by the education level. Moreover, familiarity with the route as well as not performing a secondary task contribute, although in less extent than previous attributes, to the willingness of vehicle users to release driving control. Low heterogeneity is observed for both attributes. This indicates that vehicle users do quite agree that they are not willing to release control when they are not familiar with the route and when have to perform a secondary task. Lastly, the length of the trip and the density on the road do not provide a compelling contribution to vehicle users' willingness to cede driving tasks.

Managerial recommendations

Several stakeholders have high stakes concerning automated driving. Therefore, the following guidelines are given to successfully implement automated driving. Vehicle users with a high education level or much ITS experience are most willing to release driving tasks. Therefore, it is recommended to focus marketing plans on vehicle users with high education and with much ITS experience.

The following recommendations concern transportation planning. Most support to release control can be found on highways. For this reason it is advised to stakeholders to first focus on creating strong collaborations and feasibility studies for automated driving on highways. Eventually public parties should aim at also enabling automated driving on regional roads, because this could offer highest safety benefit levels. Additionally, it is advised to enable automated driving on dense roads. Here the benefits for society are highest. The density on the road does not have much influence on the willingness of vehicle users to release control, therefore vehicle drivers will agree with this implementation plan. Stakeholders should be careful with implementing partial and high automated driving. Although vehicle users indicate that they prefer not to perform a secondary task while driving automated, many accidents have happened because drivers were distracted. In addition, vehicle users have indicated to prefer automated driving on familiar routes. However, people tend to pay less attention to the driving environment when they are familiar with the route. Hence, although highly automated technology should provide sufficient lead time to obtain the drivers attention when necessary, this is risky as small human errors could lead to fatal accidents.

DISCUSSION

This thesis adds insights in vehicle users preferences to current research. However, it has some limitations which offer opportunities for further research. Not much research is done regarding vehicle users preferences of automated driving. Literature disagrees on the gender and age levels of users that are often associated with the preference level for automated driving. The models within this research indicate that there is not so much difference between these characteristics concerning their preferences. The first limitation of the research concerns the lack of insights in interaction effects upon choice. Interaction effect could show the effect multiple levels of different attributes could have upon each other. Moreover, only people that possess a passenger vehicle driving license are taken in account. However, when fully automated driving is enabled on Dutch roads, it may also be possible that people without a driver's license can use an automated vehicle. Their preferences could influence the recommendations. Additionally, the heterogeneity within the Mixed logit models could not be explained by researching the preferences of vehicle users with differentiated gender, age, experience with ITS or education level. However, literature suggests that users' social status and financial wealth could explain the differences in preferences. Furthermore, with this research insights are gained in which situation users are willing to release control. However, for actual acceptation, also other elements are important. This includes elements such as costs, safety effects, liability, and privacy. Moreover, insights in more precise safety, traffic flow and environmental implications could lead to implementation plans that are more accurately adjusted to desired benefits.

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"Often, humans believe that their driving capabilities are superior to that of technology. However, human errors such as distraction, tiredness or drunkenness do not apply for automated vehicle technology. These are crucial issues that vehicle users could wonder about while considering to use automated driving systems. Implementing automated driving to the extent that vehicle users feel that they can release control, could eventually change mobility as we know it today."

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VOORKEUREN VAN AUTOGEBRUIKERS BETREFT GEAUTOMATISEERD RIJDEN
Implicaties voor transport- en marktplanning
I.C.H.M. (Ilse) Megens

Afstudeerprogramma:
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INLEIDING
Automobiliteit zorgt voor economische en persoonlijke groei door het mogelijk maken van dagelijkse activiteiten. Echter blijkt dat mobiliteit ook gevaren meebrengt voor de maatschappij. Dit leidt tot drie grote uitdagingen op het gebied van veiligheid, bereikbaarheid en milieu. Deze uitdagingen worden onder andere aangegaan door het gebruik van intelligente transportsystemen gebruiken. Deze systemen werken op basis van informatie en communicatie technologieën en zorgen voor een flexibeler en dynamischer verkeersysteem (SWOV, 2010). Een verder ontwikkeling om de maatschappelijke uitdagingen aan te gaan door middel van technologie, is het geautomatiseerd rijden. Dit is mogelijk gemaakt door system die de rijcontrole overnemen van de autogebruiker (Minister Schultz van Haegen, 2014). Dit resulteert in een nieuwe rolverdeling tussen de gebruiker, het voertuig en de rijomgeving. Echter, uit de literatuur blijkt dat autogebruikers niet altijd bereid zijn om controle af te geven. Ze achten zichzelf meer capabel dan technologie in het behouden van controle. Daarom is het niet zeker in welke rijsituaties autogebruikers controle willen afstaan aan systemen, en hoeveel (Muir, 1987). Echter, de bereidheid van autogebruikers om rijcontrole af te staan is een voorwaarde voor het bereiken van potentiële effecten van geautomatiseerd rijden. Daarom richt dit rapport zich op het verkrijgen van inzichten in welk niveau van automatisering en welke rijomstandigheden bijdragen aan de bereidheid van verschillende autogebruikersgroepen om rijcontrole af te staan. Dit inzicht kan gebruikt worden door transport- en marktplanners als richtlijnen voor succesvolle implementatie van geautomatiseerd rijden. Dit inzicht is verkregen door middel van het gebruik van bestaande literatuur die zich richt op geautomatiseerd rijden en hoe het gebruik van geautomatiseerde rijsystemen kan worden beïnvloed. Daarna wordt door middel van een discreet keuze-experiment bepaald welke keuzes autogebruikers maken in verschillende hypothetische rijsituaties. De verspreiding van een vragenlijst voorziet dit onderzoek van de benodigde data. Deze data wordt gemodelleerd door drie typen modellen: Multinomiaal logit model, Latenteklassemodel en het Mixed logit model.

GEAUTOMATISEERD RIJDEN

De technologie rondom geautomatiseerd rijden is gebaseerd op drie componenten. Ten eerste verschaffen in-car systemen informatie. Ten tweede voorzien applicaties voertuigen en infrastructuur van communicatiemogelijkheden. Ten derde kunnen sensoren en scanners, zonder tussenkomst van externe systemen, reageren op hun rijomgeving. Deze systemen werken samen op verschillende niveaus. Dit is getoond in Tabel 1. Op dit moment zijn alleen assisterende systemen en systemen die zorgen voor gedeeltelijk automatisering beschikbaar voor het grote publiek (Timmer, et al., 2013).

Tabel 1. Beknopte beschrijving van niveaus van automatisering (Gasser, et al., 2013)

Niveaus van automatisering	Rolverdeling van bestuurder en systemen
Alleen bestuurder	De bestuurder heeft gedurende de hele reis controle over longitudinale (versnellen/ remmen) en laterale (sturen) taken.
Geassisteerd rijden	De bestuurder heeft gedurende de hele reis controle over of de longitudinale of the laterale taken. De andere taken zijn, binnen bepaalde grenzen, uitgevoerd door het systeem.
Gedeeltelijk geautomatiseerd	Het systeem neemt controle over voor longitudinale en laterale taken (voor een bepaalde periode en/of in bepaalde situaties).
Zeer geautomatiseerd	Het systeem neemt controle over voor longitudinale en laterale taken voor een bepaalde periode en/of in bepaalde situaties.
Volledig geautomatiseerd	Het systeem neemt controle over voor longitudinale en laterale taken binnen de specificaties van de applicatie.

Geautomatiseerd rijden kan grote voordelen hebben voor veiligheid, doorstroming en milieu. Veiligheid wordt verhoog doordat systemen onveilige verkeersparticipatie voorkomen, onveilige acties tijdens het rijden voorkomen, en doordat ze de impact van een verkeersongelukken verminderen (SWOV, 2010). Dit zal voornamelijk veel effect kunnen hebben op regionale wegen, aangezien daar het aantal ongelukken het hoogst is. Ten tweede zal de doorstroming verbeterend worden doordat voertuigen geleidelijker op elkaar kunnen reageren. Ten derde zullen efficiëntere voertuigen en een efficiëntere rijomgeving, inclusief minder invloed van negatief menselijk rijgedrag, zorgen voor minder energiegebruik en uitstoot (Timmer, et al., 2013). De minister van Infrastructuur en Milieu heeft de baten van geautomatiseerd rijden erkent. Met haar voorgestelde beleid wil ze bereiken dat rond 2025, zeer geautomatiseerd en/of volledig geautomatiseerd rijden mogelijk is op het Nederlandse wegennet (Minister Schultz van Haegen, 2014).

Autorijden is een samenkomst van de bestuurder, het voertuig en de rijomgeving. Tijdens het rijden passeren voertuigen andere weggebruikers op kleine afstand. Hierdoor is er geen foutmarge en daardoor willen autogebruikers alleen controle afstaan als ze genoeg vertrouwen hebben in de geautomatiseerde systemen. Vanuit de literatuur zijn zes verschillende rijomstandigheden geïdentificeerd die invloed hebben op hoe autogebruikers het rijden ervaren. Dit zijn de weer- en lichtomstandigheden, het type weg, de drukte op de weg, de lengte van de reis, de bekendheid met de route en het wel of niet uitvoeren van een secondaire taak tijdens het rijden. Indien geautomatiseerd rijden geïmplementeerd wordt aan de hand van de voorkeuren van autogebruikers, dan het draagvlak toenemen. Dit zorgt voor meer voordelen voor veiligheid, doorstroming en milieu.

ONDERZOEKSMETHODE
Door middel van het verspreiden van een vragenlijst, kan inzicht worden verkregen in welke keuzes autogebruikers maken in de hypothetische situatie dat alle niveaus van geautomatiseerd rijden mogelijk zijn in alle rijomstandigheden. Volgens theorie zullen respondenten hun keuze tussen verschillende rijsituaties baseren op het alternatief met het hoogste nut. Deze utiliteit kan worden gemodelleerd met discrete keuze modellen. Deze modellen hebben allen hun eigen voor- en nadelen. Het Multinomiaal logit model is relatief gezien simpel, maar het houdt geen rekening met uiteenlopende voorkeuren tussen individuen of groepen van individuen. Het Latenteklassemodel houdt rekening met deze verschillen door individuen met dezelfde voorkeuren in te delen in dezelfde klas. Het Mixed logit model is nog flexibeler, deze houdt rekening met individuele voorkeuren (Greene & Hensher, 2003; Hensher, et al., 2005). De vragenlijst is verspreid mensen met een autorijbewijs in Nederland. In de vragenlijst werden de respondenten gevraagd naar hun rijervaring en rijgedrag, hun bekendheid en ervaring met intelligente systemen in de auto, hun voorkeur betreft het afstaan van rijtaken in verschillende rijsituaties door middel van stated choice antwoorden, en een aantal persoonlijke kenmerken. De vragenlijst is volledig ingevuld door 673 respondenten.

BEVINDINGEN
Het blijkt dat Mixed logit modellen de meest bruikbare inzichten geeft in de voorkeuren van verschillende gebruikersgroepen. Daarom zijn onderstaande conclusies getrokken vanuit dit type model. De resultaten laten zien dat het niveau van automatisering, het meest belangrijk is voor hun keuze om rijcontrole af te staan. Het blijkt dat alleen geassisteerd rijden of gedeeltelijk geautomatiseerd rijden de voorkeur heeft. De autogebruikers zijn neutraal over zeer geautomatiseerd rijden, maar negatief over het volledig geautomatiseerd rijden. Autogebruikers geven het liefst controle af op de snelweg, maar zijn ook niet negatief over rijden met deze systemen op een regionale weg. Daarentegen willen ze geen controle afstaan op locale wegen. Autogebruikers willen alleen geautomatiseerd rijden wanneer ze bekend zijn met de route en wanneer ze geen secondaire taak hoeven uit te voeren. De lengte van de reis en de drukte op de weg vormen vrijwel geen bijdrage aan de bereidheid van autogebruikers om rijcontrole af te staan. Er zijn grote individuele verschillen betreft de voorkeur voor het niveau van automatisering, het wegtype en de lengte van de reis. Uit de beschrijvende analyse blijkt dat de verschillen in de voorkeur om controle af te staan aan geautomatiseerde systemen, groot zijn bij verschillende geslachten, leeftijden, ervaring met verschillende intelligente systemen en bij autogebruikers met verschillende opleidingniveaus. Echter blijkt na analyse dat de onderverdeling binnen deze groepen niet de grote verschillen betreft de voorkeuren voor niveau van automatisering en rijomstandigheden verklaren.

De belangen betreft het implementeren van volledig geautomatiseerd rijden zijn hoog. Daarom zijn de volgende aanbevelingen opgesteld om bij te dragen aan succesvolle implementatie van volledig geautomatiseerd rijden. De bereidheid om gebruik te maken van volledige automatisering is erg laag. Echter, wordt aanbevolen om marktplannen te focussen op autogebruikers met een hoog opleidingsniveau en/of veel ervaring met intelligente systemen. Deze autogebruikers zijn het meest bereid om controle af te staan.

De volgende aanbevelingen hebben betrekking op de transportplanning. Het meeste draagvlak om controle af te staan is gevonden op snelwegen. Om deze reden wordt aanbevolen om sterkte samenwerkingsverbanden en haalbaarheidsstudies te creëren betreft implementatie op snelwegen. In een later stadium zou gericht moeten worden op implementatie op regionale wegen. Hier zijn de hoogste veiligheidsbaten te behalen. Verder zou gericht moeten worden op het mogelijk maken van geautomatiseerd rijden op drukke wegen, gezien hier de maatschappelijke baten het hoogst zijn. Deze rijomstandigheid heeft niet veel invloed op de bereidheid van autogebruikers om controle af te staan, daarom is aangenomen dat autogebruikers de implementatie van geautomatiseerd rijden op drukke wegen zullen accepteren. Belanghebbenden wordt aanbevolen om voorzichtig te zijn met het implementeren van gedeeltelijk en zeer geautomatiseerd rijden. Autogebruikers geven aan dat ze niet op een onbekende routes willen rijden en geen secondaire taak willen uitvoeren terwijl ze controle hebben afgegeven. Echter, literatuur geeft aan dat mensen snel afgeleid zijn op bekende routes. Ook blijkt dat mensen toch snel afgeleid zijn door een secondaire omstandigheid. Ondanks dat zeer geautomatiseerd rijden zou moeten zorgen voor genoeg tijd om de aandacht van autogebruikers te krijgen, is dit zeer riskant aangezien menselijke fouten in een klein hoekje zitten.

Dit rapport is een toevoeging aan het bestaand onderzoek. Echter zijn er een aantal beperkingen aan dit onderzoek die kunnen dienen voor nieuw onderzoek. Het blijkt dat literatuur niet overeenkomt betreffende de gebruikersgroepen die de meeste voorkeur hebben om gebruik te maken van geautomatiseerde systemen. Dit onderzoek wijst uit dat de voorkeuren niet veel verschillen. De eerste beperking van dit onderzoek is dat er geen inzicht is in de interactie-effecten van verschillende attribuut-levels. Daarnaast zijn alleen autogebruikers in bezit van een rijbewijs meegenomen in de resultaten. Echter, wanneer volledig geautomatiseerd rijden mogelijk is, is het ook mogelijk dat mensen zonder rijervaring zich kunnen laten rijden. Hun voorkeuren kunnen de resultaten beïnvloeden. Bovendien zijn de individuele verschillen binnen de Mixed logit modellen niet verklaard door het onderzoeken van mensen met verschillende geslachten, leeftijden, ervaring met intelligente systemen of opleidingsniveau. Literatuur geeft aan dat de verschillend wel verklaard zouden kunnen worden door sociale status en de financiële situatie. Daarnaast, met dit onderzoek is inzicht verkregen in welke situatie autogebruikers bereid zijn om rijcontrole los te laten. Voor werkelijke acceptatie, zijn ook andere elementen van belang. Dit omvat elementen zoals kosten, aansprakelijkheid en privacy. Bovendien zouden nauwkeurigere inzichten in veiligheid-, doorstroming- en milieueffecten kunnen leiden tot implementatieplannen die beter zijn aangepast aan de gewenste voordelen.

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