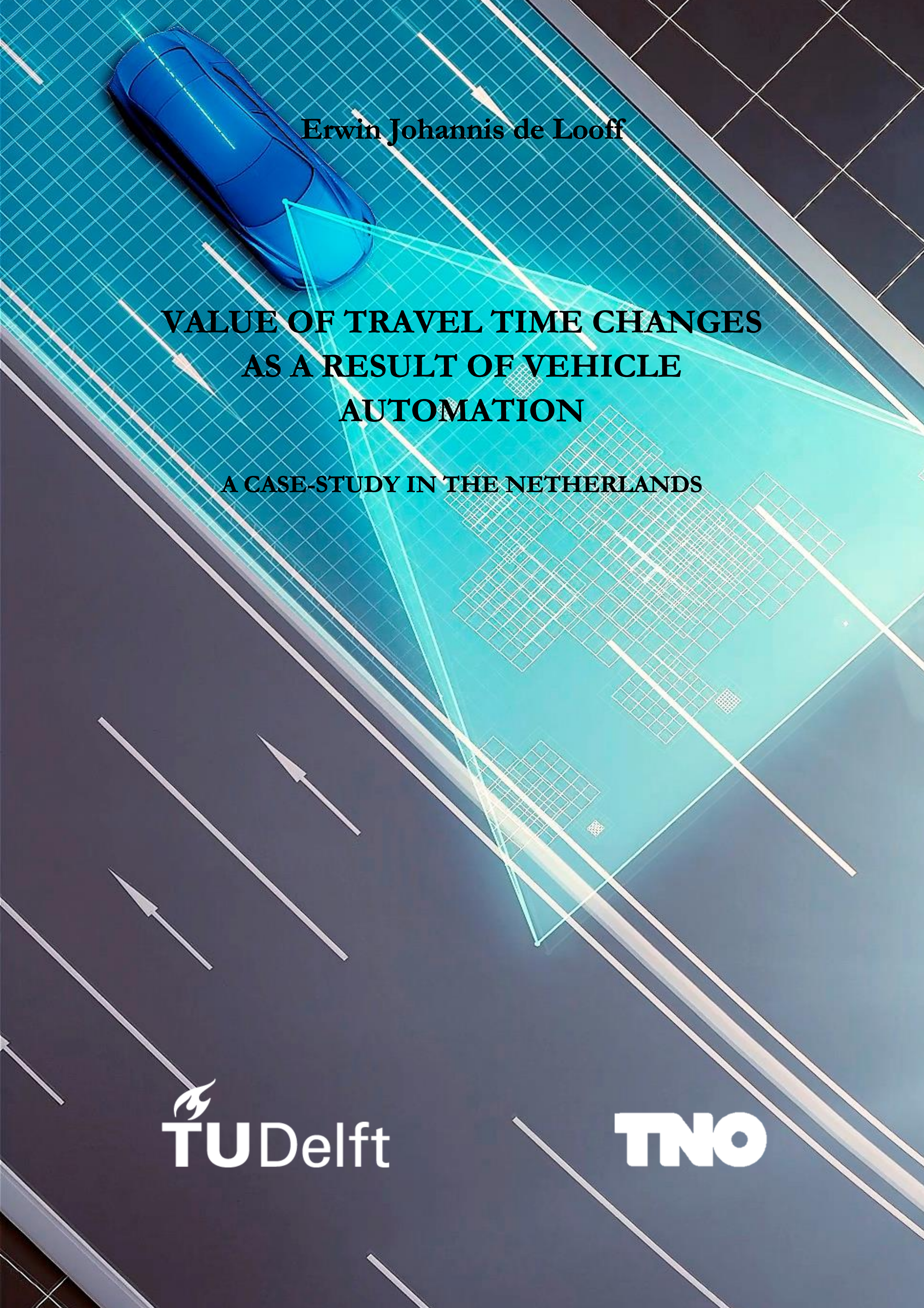

Erwin Johannis de Looff

VALUE OF TRAVEL TIME CHANGES AS A RESULT OF VEHICLE AUTOMATION

A CASE-STUDY IN THE NETHERLANDS

TU Delft

TNO

VALUE OF TRAVEL TIME CHANGES AS A RESULT OF VEHICLE AUTOMATION

A CASE-STUDY IN THE NETHERLANDS

by

Erwin Johannis de Looff

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Supervisor:	prof. dr. ir. Bart van Arem	TU Delft
Thesis committee:	dr. ir. Gonçalo Homem de Almeida Correia	TU Delft
	dr. Maaike Snelder	TNO/TU Delft
	dr. ir. Sander van Cranenburgh	TU Delft

An electronic version of this thesis is available at http://repository.tudelft.nl/.

Spatial and Transport Impacts of Automated Driving

- Luctor et Emergo (I struggle and emerge) - motto of the Province of Zeeland

PREFACE

This thesis is the end result of a seven-month research endeavour at the Applied Research Institute (TNO) and the Delft University of Technology. This work is intended for everyone who is interested in automated driving, discrete choice modelling and the value of travel time savings. A summary is written in English and in Dutch.

It was challenging regarding time, effort and knowledge to complete this Master thesis. Without the help and support – both personally and professionally – of certain persons I definitely would not have made it.

With respect to my commission I want to thank especially dr. ir. Gonçalo Homem de Almeida Correia for his supervision. His availability for meetings, his knowledge, and his enthusiasm for this research have demonstrated not only be an ideal first supervisor to me, but also a person that has made the research process more enjoyable and a person that improves the quality of the research significantly.

Next, I owe special thanks to dr. Maaike Snelder for providing me the opportunity to conduct my research at TNO. During my time at TNO I got to know a lot of fine people who made the burden of graduating lower. Besides providing me an internship, I experienced her as a passionate researcher who always was willing to think with you. Finally, I owe her a lot of thanks for the financial contribution from TNO for distributing my surveys.

Furthermore, I thank dr. ir. Sander van Cranenburgh for his feedback, enlightening comments and for helping me with the modelling. I especially appreciate that despite his occupied schedule, he was always willing to exchange some thoughts with you and to mail you back in the evening.

I thank the chairman, prof. dr. ir. Bart van Arem, for his valuable input and guidance during the meetings. His feedback was always useful.

At last, I want to thank my family, friends and roommates who always supported me and who made my study time unforgettable. Mom and dad, thank you for the (financial) support of my years of studying. My appreciation is great. To my dear friends and roommates: thank you all for these amazing years.

Erwin Johannis de Looff

The Hague, May 2017

Image frontpage: sites.ieee.org

- Luctor et Emergo (ik worstel en kom boven) - Wapenspreuk van de provincie Zeeland

VOORWOORD

Deze scriptie is het eindresultaat van een zeven maanden durende onderzoeksinspanning bij het Toegepast Natuurwetenschappelijk Onderzoeksinstituut (TNO) en de Technische Universiteit Delft. Dit werk is bedoeld voor iedereen die geïnteresseerd is in automatisch rijden, discrete keuzemodellen en reistijdswaardering. Een samenvatting is geschreven in het Engels en in het Nederlands.

Het was een uitdaging qua tijd, moeite en kennis om deze Masterscriptie te voltooien. Zonder de hulp en steun – op zowel persoonlijk vlak als op professioneel vlak – van bepaalde personen zou ik het nooit hebben voltooid.

Met betrekking tot mijn commissie wil ik speciaal dr. ir. Gonçalo Homem de Almeida Correia bedanken voor zijn supervisie. Zijn bereidheid voor het houden van meetings, zijn kennis en zijn enthousiasme voor dit onderzoek hebben laten zien dat hij niet alleen een ideale eerste begeleider voor mij was, maar dat hij ook een persoon is die het onderzoeksproces aangenamer maakt en die de kwaliteit van het onderzoek aanzienlijk doet laat stijgen.

Daarnaast ben ik veel dank verschuldigd aan dr. Maaike Snelder door mij de gelegenheid aan te bieden om mijn onderzoek bij TNO te komen doen. Tijdens mijn tijd bij TNO heb ik veel fijne mensen leren kennen die de last van het afstuderen deden doen afnemen. Naast het aanbieden van een stage heb ik haar ervaren als een gepassioneerd onderzoekster die altijd bereid was met je mee te denken. Als laatste ben ik haar veel dank verschuldigd voor de financiële bijdragen vanuit TNO voor het verspreiden van mijn enquêtes.

Verder bedank ik dr. ir. Sander van Cranenburgh voor zijn feedback, verlichtende commentaar en voor de hulp bij het modelleren. Ik waardeerde het ten zeerste dat ondanks zijn drukke agenda hij altijd bereid was om met je van gedachte te wisselen dan wel in de avond terug te mailen.

Ik dank de voorzitter, prof. dr. ir. Bart van Arem voor zijn waardevolle input en begeleiding tijdens de meetings. Zijn feedback was altijd nuttig.

Als laatste, bedank ik graag mijn familie, vrienden en huisgenoten die mij altijd steunden en die mijn studietijd onvergetelijk hebben gemaakt. Mama en papa, bedankt voor de (financiële) steun tijdens mijn studiejaren, mijn waardering is groot. Aan mijn goede vrienden en huisgenoten: dank jullie wel voor deze fantastische jaren.

Erwin Johannis de Looff
's Gravenhage, mei 2017

SUMMARY

The Netherlands faces many challenges regarding mobility. Strengthened by the economic recovery the number and intensity of traffic increases due to more car trips. This is accompanied by negative feedback on energy consumption, economic growth and the environment. A possible solution to cope with this problem automated driving. Automated vehicles (AVs) have the possibility to form platoons, which reduces the required space and polluted emissions. Besides, most traffic accidents are caused by human factors, which could be eliminated by a computer-driven car. An additional benefit of (full-)automated driving is that one can perform activities while driving on the road. Examples are working or having leisure time. However, it is not yet investigated how a trip using an AV as main mode is experienced compared to a trip using a conventional car. This research tries to bridge this knowledge gap by researching the following problem: '*There is insufficient knowledge in how people will experience their trips when driving in a full-automated vehicle in relation to driving in a conventional vehicle in the Netherlands.*'.

A possibility to measure this perception is to determine the value of travel time savings (VOTT) of the users of automated vehicles. This has scientific value since the VOTT is used as important parameter to monetise travel time savings in cost-benefit analysis. Besides, the VOTT is used as input in traffic models. The VOTT captures a traveller's willingness to pay for travel time savings (WTP). If the VOTT for AV users is different than for conventional car users, the importance of newly built infrastructure could change. In case of a higher VOTT, travel time savings are economically more important, while a lower VOTT reduces the importance of travel time savings and new infrastructure, ceteris paribus. The expectation is that the VOTT of AV users is lower than the VOTT of conventional car users. This expectation is based on the assumption that one is able to perform activities while driving in an AV. Because an AV user is able to work or to have leisure time instead of driving, an increase in travel time will be experienced less negatively. Thus, the aim of the research is defined as follows: '*To explore how people in the Netherlands experience a trip in a full-automated vehicle compared to a trip in a conventional car.*'.

The demographic focus of this research is the Netherlands, since every country determines its own VOTTs. It is, for simplicity reasons, assumed that the AV is privately owned, and its valuation is compared to the conventional car only. This brings us to the main research question, which is: '*How do full-automated vehicle users experience a trip compared to conventional car users for the trip purpose home-to-work in the Netherlands?*'.

Methodology

Different methods can be used to determine VOTTs. Given the nature of the research it is chosen to combine stated preference (SP) experiments and an exploratory factor analysis (EFA). The main advantages of an SP experiment are that it is able to cope with non-existing alternatives, the VOTT can be statistically derived from discrete choice models and it allows respondents to choose between alternatives rather than rating alternatives. An exploratory factor analysis was chosen, because it was expected that psychological factors regarding automated driving influence the decision-making. The EFA will be executed by means of a latent variable model. A hybrid choice modelling approach has been applied, where the latent variable model and the discrete choice models are estimated sequentially.

Two experiments were held. The first SP experiment compares two types of AVs to the conventional car. The second SP experiment substitutes the AVs for chauffeur-driven (CH) cars. At the end the experience of a trip in an AV is compared to the experience of a trip in a chauffeur-

driven car. Two AV/CH variants are defined: an AV/CH with office interior and an AV/CH with leisure interior. This has been done to explore if there is a difference in trip experience when one is working or when one is having leisure time. The SP experiments explore the classical instrumental variables travel time, travel costs and walking time. Travel company [travel alone, travel with family/friends] and AV/CH-office activity [working extra time, saving time at the office] are added as additional attributes in the SP experiment.

Two principles of discrete choice modelling exist: random utility maximisation (RUM) based and random regret minimisation (RRM) based. RRM models assume that respondents choose the alternative that generates least regret, while RUM models assume that respondents pick the alternative that produces most utility. It is chosen to use the RUM principle in this thesis, since it is easier to derive the VOTT estimates and the VOTT estimate is more complete. Besides, RUM is a more commonly used methodology and it is expandable with extensions like latent variable models.

In total each SP experiment (AV-case and chauffeur-case) included 12 different choice sets. Each choice task included the same travelling context, which is the morning peak (from home to work). The final survey included further 18 attitudinal statements that had to be rated. The last part of the survey included questions about socio-economic characteristics of the respondents. Each survey (AV-case and chauffeur-case) was distributed through different large online panels.

Data collection & analysis

Eventually, 252 useful respondents completed the AV survey, and 242 useful respondents were collected with the chauffeur survey. The AV sample represents the Dutch population better than the chauffeur sample. Each dataset contained so-called non-traders; respondents who always choose the same alternative (e.g. 12 times conventional car) (Hess, Rose, & Polak, 2010). Non-traders can influence parameter estimations, so each discrete choice model was estimated with the full sample (e.g. all AV-case respondents) and with the sample excluding non-traders (all AV-case respondents minus all non-trading respondents). It appeared that mostly (>40%) retired, 'other' employed, and/or low educated respondents perform non-trading behaviour. About 72% of the non-traders in the AV-case chose always the conventional car alternative, while almost 87% of the non-traders in the chauffeur-case opted always the conventional car.

Per case three different types of choice models were estimated. These are the multinomial logit (MNL) model, nested logit (NL) model and mixed logit (ML) model. The goal of estimating a MNL model is to find the model parameters (*β*s) that provide information about the preferences of the decision makers (McFadden, 1974). The MNL model is the most commonly used model. NL is an approach that generalises the MNL model by allowing correlation between the non-observed utilities of groups of alternatives (Hensher & Greene, 2002). The mixed logit allows the parameter vector β used in the computation of the utility to be randomly distributed rather than fixed (Hess, Bierlaire, & Polak, 2005).

Regarding the AV-case and the chauffeur-case, the results of the models estimated using the data excluding non-traders were more stable and consistent than the results of the full sample models. Therefore, the full-sample models are not used for answering the research questions. Figure 0.1 visualises that the AV-office user has a mean VOTT of €5.39 per hour (-33.0% compared to car), the AV-leisure user has a mean VOTT of €10.84 per hour (+34.9% compared to car), and the car travellers' mean VOTT is €8.04 per hour. Furthermore, significant standard deviations were estimated in the ML models, which means that heterogeneity exists in mode-specific time parameter, this also in the VOTTs. Heterogeneity was also measured in the unobserved preference for AVs.

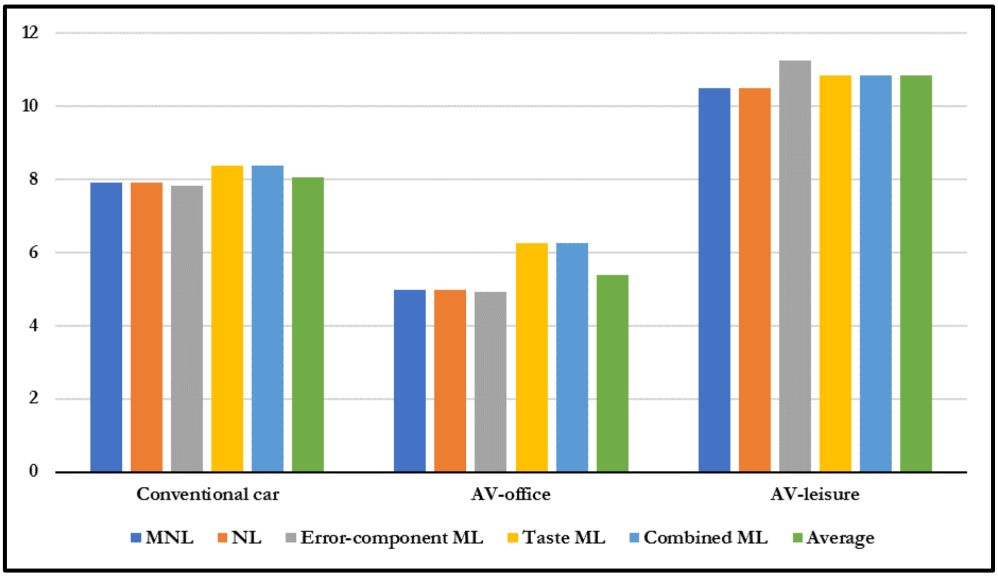

Figure 0.1: Mean VOTT estimates of the AV-case (excl. non-traders) in [€/hr].

The mean VOTTs of the chauffeur-case estimated with the models using data excluding non-traders are stable and consistent, and were used for further analysis. Figure 0.2 shows the estimated VOTTs per user group of the chauffeur-case. The CH-office user has an average VOTT (€4.57 per hour) and is in line with the average VOTT of AV-office users. The average VOTT of CH-leisure users is €7.34 per hour and is about €3.50 lower than the average VOTT of AV-leisure users. At last, the average VOTT of the conventional car users is €8.54 per hour, which is in line with the average VOTT of conventional car users found using the AV-dataset. Significant standard deviations were estimated, which indicates that heterogeneity exists in the estimated VOTTs and in the unobserved preference for AVs.

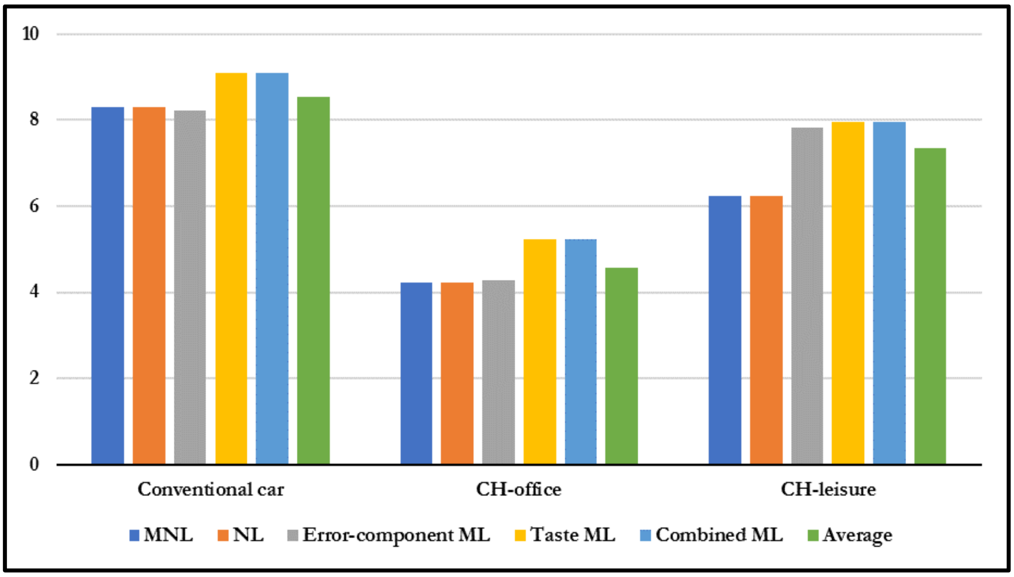

Figure 0.2: Mean VOTT estimates of the CH-case (excl. non-traders) in [€/hr].

Furthermore, the results showed that current car-poolers, young adults (<26 years) and retirees have a preference for automated driving, while bus/metro/tram (BMT) users, car users, full-time workers, part-time workers and elderly people (>60 years) tend to opt for the conventional car. However, it was concluded that mainly, respondents who are older, low educated, retired and/or 'other' employed showed non-trading behaviour for conventional cars, which conflicts with the finding that retirees prefer AVs.

Also the importance of attitudinal factors has been shown in this study. It appears that a positive attitude towards the conveniences of automated driving and the safety of automated driving influence the choice behaviour in favour of the AVs. However, for people who do not trust the concept of automated driving a preference for the conventional car was observed.

It was unexpected that the VOTT of AV-leisure users is higher than the VOTT of conventional car users. Different explanations can be given. Firstly, respondents cannot imagine what having leisure time in an AV includes. Working when being in transport is already a common among travellers (e.g. calling in a car, working on laptop in the train), while having leisure activities is less common. A second explanation is that the benefits of travelling in an AV-leisure in the morning was not explained well enough. For example, one could eat breakfast, put on make-up or read the newspaper in the AV-leisure, which reduces the time needed in the morning and increases the time in bed. At last, reading, watching a movie or gaming is not an activity that is preferred in the morning. This could result in a higher VOTT. So it is concluded that further research to the VOTT of AV-leisure users is required.

The VOTT estimates could have major effects on the current CBA methodology and thus on policy making. A lower VOTT means that people are willing to pay less money for travel time savings, thus longer travel times are experienced less negatively. Since the VOTT is the most important parameter to monetise travel time savings in CBAs, a decrease of this parameter would imply that travel time savings result in less benefits. However, a lower VOTT could result in a higher travel demand and more trip generations. This would lead to more benefits.

On the other hand, since the AV is an attractive mode of transport, the amount of vehicles on the road could increase. This results in more congestion, which negatively influences the environment. However, AVs are able to form platoons, which potentially increase the road capacity. This would result in fewer traffic jams.

In the case the benefits will be lower when using AVs, it could mean that infrastructural projects are less efficient or not feasible anymore. This raises the question whether creating new road infrastructure is useful, since the VOTT indicates that the welfare loss due to congestions is reduced. Nevertheless, new infrastructure serves the purpose to improve the travel time reliability as well. This aspect was out of the scope of this research, so this question cannot be answered. So, how automated driving will influence CBAs and thus policy making is unknown, and is a topic for further research.

Conclusion & recommendations

With the results of this study the main question '*How do full-automated vehicle users experience a trip compared to conventional car users for the trip purpose home-to-work in the Netherlands?*' can be answered. AV-office travellers are willing-to-pay less money to reduce their journey time compared to conventional car travellers, while AV-leisure users tend to pay more money to reduce their travel time compared to conventional car users. This means that AV-office travellers experience a trip more positively in the morning due to productivity opportunities compared to conventional car users, while for AV-leisure users it is the other way around.

However, when a leisure-vehicle is driven by a human instead of a computer, a trip is experienced more positively. The trip experience when being driven by a computer or by a human in an office-vehicle is almost the same.

Furthermore, positive attitudes towards automated driving increases the positive valuation of AVs regardless of interior type. At last, car-poolers and young adults tend to gain more utility from an AV with respect to the normal car.

This research was an exploration of how the VOTT of full-automated vehicle travellers will develop in the future. The sample size was 252 respondents and some population groups were oversampled, so it is recommended to do more research with a larger sample and a more representative sample. Next, it is recommended to do a study regarding the VOTT of partial-automated vehicles, since these types are sooner available on the market. Furthermore it is recommended to do more research on the VOTT of AV-leisure users, since the outcome of this results was not in line with the expectation. Because travel time becomes less important for AV travellers it is recommended to do further research to the importance of travel time reliability. It is not known if a longer travel time due to more distance is experienced the same as a longer travel time due to congestion. Therefore, it is recommended to investigate this in a next study as well.

Another recommendation is about the methodology. In the ML models, due to time constraints, a normal distribution was used, which has the disadvantage of estimating negative VOTT estimates for some individuals. So, it is recommended to do another study with ML models using a lognormal, triangular or S_B distribution. The next recommendation is to do further research about the impact of automated driving compared to current modes of transport (e.g. train, bike, BMT), since this impacts policy making. The last recommendation is to conduct further research to the effects of the VOTT of AV users on CBAs such that decision-making by politicians can be improved.

SAMENVATTING

Nederland wordt geconfronteerd met vele uitdagingen betreffende mobiliteit. Gesterkt door het economisch herstel neemt het aantal en de intensiteit van files weer toe. Dit gaat gepaard met negatieve gevolgen voor het energie verbruik, de economische groei en het milieu. Een mogelijke oplossing voor dit probleem is automatisch rijden. Automatische voertuigen (AV's) hebben de mogelijkheid om platoons te vormen die het ruimtegebruik en de uitstoot van broeikasgassen verminderen. Daarnaast gebeuren ongelukken dikwijls door foutief menselijk handelen, wat in theorie geëlimineerd wordt door het automatische rijden. Een ander bijkomend voordeel van automatisch rijden is dat een activiteit uitgevoerd kan worden tijdens het rijden zoals werken of een vrijetijdsbesteding. Echter, het is nog niet onderzocht hoe een rit met een AV wordt ervaren ten opzichte van een trip met een conventionele auto. Dit onderzoek springt in deze kennislacune door het volgende probleem te onderzoeken: *'Er is onvoldoende kennis over hoe mensen een rit in een volautomatisch voertuig ervaren in relatie tot het rijden in een conventionele auto in Nederland.'*.

Een mogelijkheid om dit te meten is het bepalen van de reistijdswaardering (RTW) van AV-gebruikers. Dit heeft wetenschappelijke waarde, doordat de RTW een belangrijk kengetal is voor het monetariseren van reistijdswinsten in maatschappelijke kosten-batenanalyses (MKBA). Daarnaast wordt de RTW ook als parameter gebruikt in verkeersmodellen. De RTW impliceert een monetaire waarde wat een reiziger bereid is te betalen om zijn reistijd te verkorten. Als bijvoorbeeld de RTW van AV-gebruikers lager is dan voor autogebruikers dan zou dit de mate van belang van nieuwe infrastructuur kunnen veranderen. In het geval van een hogere RTW is een reistijdswinst economisch belangrijker, terwijl bij een lagere RTW het inverse effect aantreedt mits ceteris paribus. De verwachting is dat de RTW voor AV-reizigers lager zal zijn dan de RTW van autogebruikers, doordat er tijdens het rijden andere activiteiten uitgevoerd kunnen worden. Uiteindelijk is het doel van dit onderzoek als volgt geformuleerd: *'Onderzoeken hoe mensen in Nederland een rit in een volautomatisch voortuig ervaren vergeleken met een rit in een conventionele auto.'*.

De demografische focus van dit onderzoek is Nederland, omdat elk land andere RTW's hanteert. Om het verder te vereenvoudigen is er gekozen om te focussen op private AV's. Na deze afbakeningen kan de hoofdvraag geformuleerd worden, die als volgt luidt: *'Hoe ervaren volautomatische voertuigreizigers een rit vergeleken met conventionele autoreizigers voor het reisdoel huis-naar-werk in Nederland?'*.

Methodologie

Er bestaan verschillende methodes om de RWT te bepalen. Gegeven de aard van het onderzoek is er gekozen om stated preference (SP) experimenten te combineren met een explorerende factor analyse (EFA). De grootste voordelen van een SP experiment is dat het kan omgaan met niet-bestaande alternatieven, de RWT statistisch afgeleid kan worden middels discrete keuzemodellen en het staat toe dat respondenten kiezen tussen alternatieven in plaats van dat ze alternatieven moeten rangschikken. Een EFA wordt toegepast, omdat de verwachting is dat psychologische factoren met betrekking tot automatisch rijden van invloed zullen zijn op het keuzeproces. De EFA zal worden uitgevoerd middels een latent variabele model. Een hybride keuze modeleermethode zal worden toegepast, waarbij het latente variabele model en de discrete keuzemodellen sequentieel geschat worden.

Twee experimenten zijn uitgevoerd. Het eerste SP experiment vergelijkt twee soorten AV's met de conventionele auto. Het tweede experiment verving de AV's voor chauffeur-gereden (CH) auto's. Aan het einde van de studie wordt de waardering van een rit in een AV vergeleken met een rit in een chauffeur-gereden auto. Twee AV/CH varianten zijn gedefinieerd: een AV/CH voertuig met

kantoorinterieur en een AV/CH voertuig met vrijetijdsinterieur. De gedachtegang hierachter is om te onderzoek of er een verschil in ritervaring zit als iemand aan het werk is of als iemand zijn tijd vrij kan besteden. De SP experimenten verkennen klassieke attributen als reistijd, reiskosten en looptijd. Reisgezelschap [reis alleen, reis met vrienden/familie] en AV/CH-kantoor activiteit [werk extra tijd, reduceer tijd op kantoor] zijn toegevoegd als extra attributen.

Twee soorten discrete keuzemodellen worden toegepast: random nutmaximalisatie (RUM) en random spijtminimalisatie (RRM). RRM modellen veronderstellen dat respondenten het alternatief kiezen dat het minste spijt genereert, terwijl RUM modellen van het hoogste nut uitgaan. De focus van dit onderzoek ligt op het schatten van RTW's en dit is makkelijker en completer bij het gebruik van RUM modellen. Daarnaast zijn RUM modellen een vaker toegepaste techniek en zijn ze uit te breiden met een latent variabele model.

Elk experiment bevat in totaal 12 verschillende keuzesets. Elke keuzeset heeft een ochtendspits (huis-naar-werk) reiscontext. De uiteindelijke enquêtes bevatten ook 18 attitude gerelateerde stellingen en extra vragen met betrekking tot sociaal-demografische kenmerken. Elke enquête is gedistribueerd middels verschillende grote online internetpanels.

Data verzameling & analyse

Uiteindelijk hebben 252 bruikbare respondenten de AV-enquête ingevuld en 242 bruikbare respondenten zijn verzameld met de chauffeur-enquête. De AV-steekproef representeert de Nederlandse bevolking beter dan de chauffeursteekproef. Elke dataset bevat zogenoemde non-traders, wat neerkomt op mensen die altijd hetzelfde alternatief kiezen (Hess et al., 2010). Non-traders kunnen de parameterschatting beïnvloeden. Door deze reden wordt elk discreet keuzemodel geschat met de volledige steekproef en met de steekproef exclusief non-traders. Het bleek dat meestal (>40%) respondenten die gepensioneerd zijn, 'anders' als werkstatus hebben, ouder zijn en/of lager opgeleid zijn meer non-trading gedrag vertonen. Ongeveer 72% van de non-traders koos altijd de conventionele auto van de AV-casus, terwijl 87% van de non-traders altijd de conventionele auto koos in de chauffeur-casus.

Per case zijn er drie verschillende keuzemodellen geschat. Deze zijn het multinomiale logit (MNL) model, het geneste logit (NL) model en het gemixte logit (ML) model. Het doel van een MNL model is om modelparameters te vinden die ons van informatie voorzien betreffende de voorkeuren van de respondenten (McFadden, 1974). Het MNL model is het meest toegepaste model. NL is een toepassing die een correlatie toelaat tussen niet-geobserveerde nutten van groepen alternatieven (Hensher & Greene, 2002). Het ML model staat toe dat de marginale nutsvector willekeurig wordt getrokken uit een verdeling in plaats van dat deze waarde vast is (Hess et al., 2005).

De resultaten van de modellen die geschat zijn met de data exclusief non-traders waren stabieler en consistenter dan de resultaten van de modellen die geschat zijn met de volledige dataset. Hierdoor, worden de volledige-steekproef modellen niet gebruikt voor het beantwoorden van de onderzoeksvraag. Figure 0.1 laat zien dat de AV-kantoorgebruiker een gemiddelde RTW heeft van €5.39 per uur (-33,0% vergeleken met de auto), de AV met vrijetijdsinterieur gebruikers hebben een gemiddelde RTW van €10,84 per uur (+37,9% vergeleken met de auto) en de gemiddelde RTW van autogebruikers is €8,04 per uur. Verder zijn er significante standaard deviaties geschat in de ML modellen, wat betekent dat heterogeniteit bestaat in de niet-geobserveerde preferentie voor AV's en in de tijdparameters. Dit betekent dat er ook heterogeniteit bestaat in de RTW's.

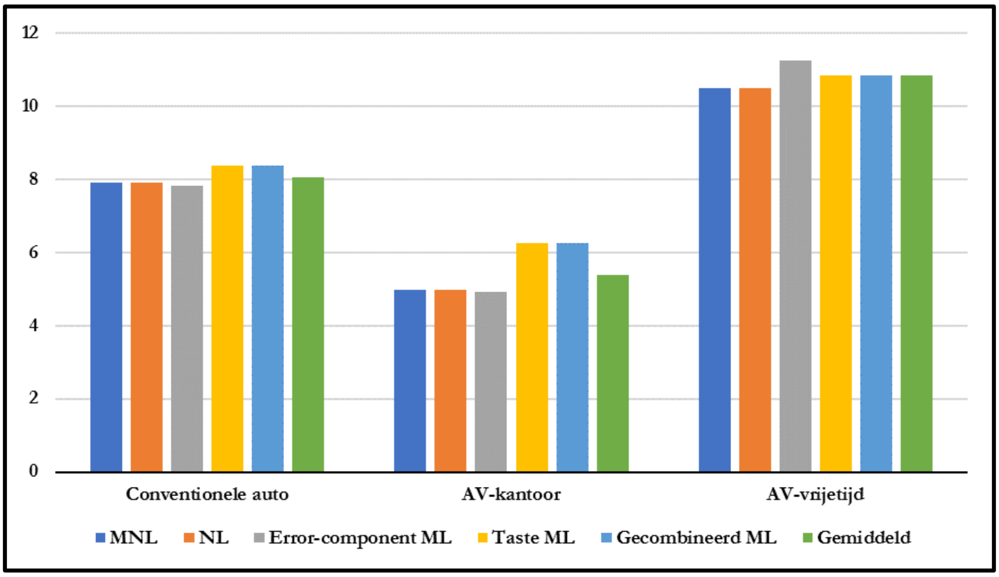

Figure 0.1: Gemiddelde RTW schattingen van de AV-casus (exclusief non-traders) in [€/hr].

De gemiddelde RTW's van de chauffeur-casus die zijn geschat door de modellen die gebruik maken van de volledige dataset zijn niet stabiel en niet consistent. De geschatte RTW's middels de modellen die gebruik maken van de dataset exclusief de non-traders zijn wel stabiel en consistent en zijn gebruikt voor verdere analyses. Figure 0.2 laat de geschatte RTW's per reizigersgroep van de chauffeur-casus zien. De CH-kantoorgebruiker heeft een gemiddelde RTW (€4,57 per uur) die dicht in de buurt van de RTW van de AV-kantoor gebruiker ligt. De gemiddelde RTW van de CH-vrijetijdgebruiker is €7,34 per uur en is ongeveer €3,50 lager dan de gemiddelde RTW van de AV-vrijetijdgebruiker. Als laatste, de gemiddelde RTW van de conventionele autogebruiker is €8,54 per uur, wat overeenkomstig is met de RTW van conventionele autogebruikers uit de AV-casus. Significante standaard deviaties zijn gevonden, wat aangeeft dat heterogeniteit bestaat in de geschatte RTW's en in de niet-geobserveerde preferentie voor AV's.

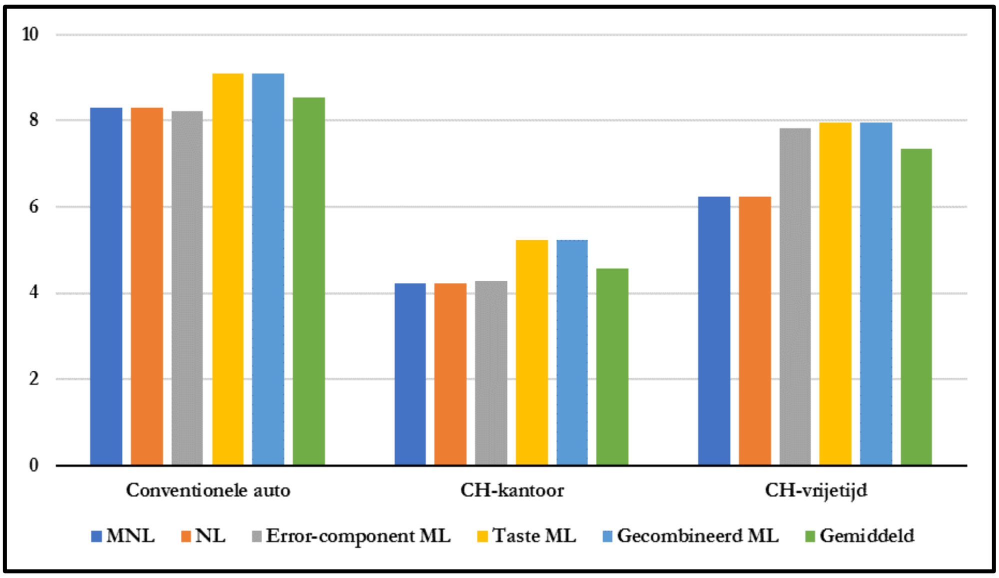

Figure 0.2: Gemiddelde RTW schattingen van de chauffeur-casus (exclusief non-traders) in [€/hr].

Verder vertellen de resultaten ons dat huidige carpoolers, jongvolwassenen en gepensioneerden een voorkeur hebben voor AV's, terwijl bus/metro/tram (BMT) gebruikers, autogebruikers, ouderen, voltijdwerkers en deeltijdwerkers een voorkeur hebben voor de gewone auto. Echter, het was geconcludeerd dat voornamelijk ouderen, lager opgeleiden, gepensioneerde en 'anders' werkenden non-trading gedrag voor conventionele auto's vertonen. Dit conflicteert met de uitkomst dat gepensioneerden een voorkeur hebben voor AV's.

Ook het belang van attitudes is aangetoond met deze studie. Het blijkt dat een positieve houding jegens de gemakken van het automatisch rijden en de veiligheidsaspecten van het automatisch rijden het keuzegedrag voor AV's positief beïnvloedt. Echter, mensen die het concept automatisch rijden niet vertrouwen hebben een voorkeur voor de conventionele auto.

Het was onverwacht dat de RTW van de AV-vrijetijdgebruikers hoger is dan de RTW van de conventionele autogebruikers. Verschillende toelichtingen kunnen hiervoor worden gegeven. Allereerst zouden respondenten het niet goed kunnen voorstellen wat vrijetijd hebben in een AV inhoudt. Werken terwijl je aan het reizen bent is momenteel al een normale bezigheid (vb. bellen in de auto en werken op je laptop in de trein) terwijl voor vrijetijd hebben dit minder is. Een tweede verklaring is dat de voordelen van het reizen met een AV-vrijetijd in de ochtend niet goed zijn uitgelegd. Je zou bijvoorbeeld kunnen ontbijten, make-up op kunnen doen of de krant lezen in een AV-vrijetijd. Dit resulteert in dat je minder tijd in de morgen nodig hebt, dus dat je langer in bed kunt liggen. Een laatste verklaring zou kunnen zijn dat men lezen of film kijken of gamen niet prefereert in de ochtend. De conclusie kan getrokken worden dat er meer onderzoek naar de RTW van AV-vrijetijd nodig is.

De gevonden gemiddelde RTW's zouden een grote impact kunnen hebben op de huidige MKBA methodologie en dus op het maken van beleid. Een lagere RTW betekent dat mensen bereid zijn minder geld te betalen om hun reis te verkorten, wat inhoud dat langere reistijden minder negatief worden ervaren. Aangezien de RTW de belangrijkste parameter is om reistijdwinsten te monetariseren in een MKBA zou een verlaging van deze parameter impliceren dat reistijdwinsten minder baten opleveren. Echter, een lagere RTW zou ook kunnen resulteren in meer vraag naar mobiliteit en meer ritproductie. Dit zou weer resulteren in meer baten.

Aan de andere kant, omdat het AV een aantrekkelijk vervoersmiddel is, zou het aantal voertuigen op de weg kunnen toenemen. Dit zou kunnen resulteren in meer files wat een negatief effect heeft op het milieu. Aan de andere kant kunnen AV's platoons vormen wat in potentie de wegcapaciteit zou doen toenemen. Dit zou weer resulteren in minder congestie.

In het geval dat de baten lager zijn als er AV's rondrijden, zou dit kunnen betekenen dat infrastructurele projecten minder haalbaar of niet meer haalbaar zijn. Dit roept de vraag op of het aanleggen van nieuwe weginfrastructuur nog wel zin heeft aangezien de RTW aanduidt dat het welvaartsverlies door files minder is. Desalniettemin, nieuwe infrastructuur dient ook het doel de reistijdbetrouwbaarheid te vergroten. Dit aspect viel echter buiten de scope van dit onderzoek en zal met deze studie niet beantwoord kunnen worden. Al met al is het onbekend hoe automatisch rijden MKBA's en dus het maken van beleid zal beïnvloeden en is een onderwerp voor verder onderzoek.

Conclusie & aanbevelingen

Met de resultaten van deze studie kan de hoofdvraag '*Hoe ervaren volautomatische voertuigreizigers een rit vergeleken met conventionele autoreizigers voor het reisdoel huis-naar-werk in Nederland?*' beantwoord worden. AV-kantoorreizigers zijn bereid minder geld te betalen om hun reistijd te verkorten vergeleken met conventionele autoreizigers, terwijl AV-vrijetijdreizigers juist bereid zijn meer geld te betalen om hun reistijd te verkorten vergeleken met conventionele autogebruikers. Dit betekent dat AV-kantoorreizigers, door de mogelijkheid tot werken, een rit positiever ervaren in de ochtendspits ten opzichte van conventionele autogebruikers, terwijl voor AV-vrijetijdgebruikers het omgekeerde geldt. Echter, als een vrijetijdsvoertuig wordt gereden door een mens in plaats van een computer wordt een rit positiever ervaren. Voor de reiservaring in een kantoor-voertuig maakt het niet uit of er gereden wordt door een computer of een mens.

Verder draagt een positieve houding jegens automatisch rijden bij aan een positieve waardering voor dit vervoersmiddel. Als laatste ervaren carpoolers, jongvolwassenen en gepensioneerden meer nut door het gebruik van een AV ten opzichte van een conventionele auto.

Dit onderzoek was een verkenning in hoe de RTW van volautomatische voertuigreizigers zich zal ontwikkelen. Aangezien de steekproef bestond uit 252 respondenten en sommige populatiegroepen over- of onder representatief waren, is het aanbevolen om een volgend onderzoek te doen met een grotere en meer representatievere steekproef. Verder wordt het aanbevolen om een onderzoek te doen naar de RTW's van de gebruikers van halfautomatische voertuigen aangezien dit type voertuig eerder op de markt zal verschijnen. Daarnaast is het ook aanbevolen om vervolgonderzoek te doen naar de RTW van AV-vrijetijdgebruikers, aangezien de uitkomsten van dit onderzoek strookt met de verwachting. Doordat reistijd minder belangrijk wordt voor AV-gebruikers is het aanbevolen om verder onderzoek te doen naar de mate van belangrijkheid van reistijdbetrouwbaarheid. Daarnaast is het onbekend of een langere reistijd door een langere afstand hetzelfde wordt ervaren als een langere reistijd door file. Het is daarom ook aanbevolen om dit te onderzoeken in de volgende studie.

Een volgende aanbeveling betreft de methodologie. Bij de ML modellen is, door tijdsbeperkingen, gebruik gemaakt van de normaalverdeling welke het nadeel heeft om een negatieve RTW te schatten voor individuen. Dus het is aanbevolen om in een vervolgstudie met ML modellen een logaritmische normaalverdeling, driehoekige verdeling of een S_B verdeling toe te passen. Een volgende aanbeveling is om onderzoek te doen naar de impact van automatisch rijden op al bestaande vervoersmiddelen zoals de trein, fiets en BMT. De impact van automatisch rijden kan namelijk verschil maken als het aankomt op beleid. De laatste aanbeveling is om verder onderzoek te doen naar de effecten van de RTW van AV-gebruikers op MKBA's zodat de besluitvorming wordt verbeterd.

TABLE OF CONTENTS

TABLE OF FIGURES

TABLE OF TABLES

1 INTRODUCING THE RESEARCH

Technological developments take place every day throughout every sector. In the transportation sector technological progress is made as well, especially in automated driving. Examples of companies that experiment with automated vehicles (AVs) are Tesla, Google, and Volvo (Google, 2016; Tesla, 2016; Volvo Cars, 2016). But, how will people experience their trips in an automated vehicle? A tool to measure this is the Value of Travel Time (VOTT). Currently, the effect of automated vehicles on the VOTT of its travellers is unknown. The VOTT is often used in assessing transportation investments, travel behaviour and travel assignment models (Tseng & Verhoef, 2008). Therefore, the effect of AVs on the VOTT is important to know. Theory mentions that the VOTT should decrease in an AV by reason of productivity gains. However, a first research found that the VOTT increases compared to its manually driven counterpart (Yap, Correia, & van Arem, 2016). Thus the problem is that there is insufficient knowledge in the effect on the VOTT of AV users compared to conventional car users in the Netherlands. This thesis aims to find an answer on how the travellers experience a trip in a full-automated vehicle compared to the conventional vehicle in the Netherlands.

In the following subsection (§1.1) an elaborated explanation of the problem is given concluded with a final problem statement. Then in §1.2 the relevance and aim of this research are explained. Subsection 1.3 defines the scope of this research. Subsequently the main research question and its sub questions are defined and explained (§1.4). At last, the outline of the thesis is given in subsection 1.5.

1.1 PROBLEM DEFINITION

In the last decades the Netherlands encountered a significant increase in welfare. The increased prosperity had clear effects on the demand for mobility; an increase in transportation performance of 30% between 1990 and 2010 (CBS Statline, 2015b). Underlying impact is that an extensive growth of passenger cars occurred in the Netherlands, from 5.1 million in 1990 to over 8.1 million in 2016. Including all other driving vehicles the total amount of vehicles in the Netherlands equals almost 11 million (CBS Statline, 2016d). As a result of an increased need in mobility an increment in traffic jams occurred (Bogaerts et al., 2004). Greenwood & Bennett (1996) mention that congestion leads to more travel time, higher vehicle operating costs and more hazardous emissions, which results in big societal costs and a worsening environment. The extra required travel time can be seen as non-productive time, which negatively influences the GDP when travelling during work time (Stopher, 2004). Since the Netherlands has a big transportation and logistics sector, (CBS, 2016) it is even more important to reduce travel time costs as much as possible.

That a relation exists between traffic performance and thereby the degree of congestion and welfare can be seen in Figure 1.1. This figure shows that the economic recession in 2008 had a large influence in reducing total congestion. However, with the economic recovery the total congestion starts to increase again.

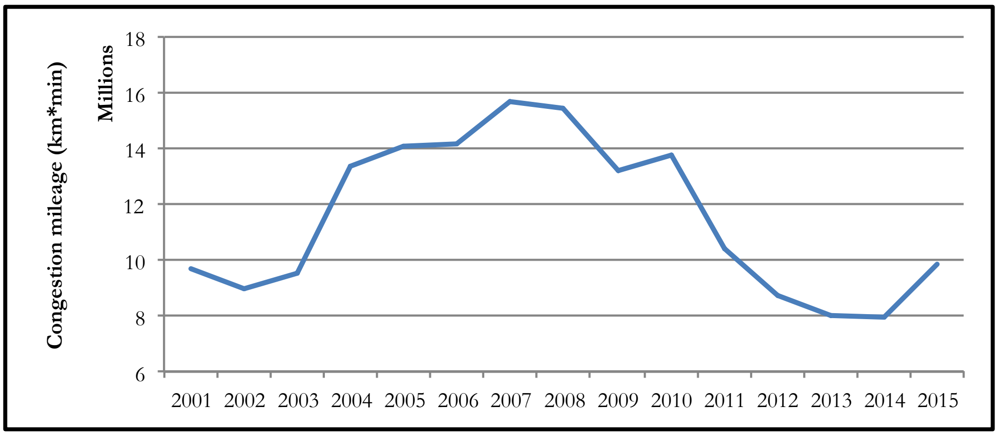

Figure 1.1: Congestion mileage in the Netherlands 2001-2015 (VID, 2016).

However, welfare is not the only factor that influences the need for mobility. The production of demand for mobility is part of a bigger mechanism depending on multiple factors. Important factors that impact mobility growth are the transportation costs, social-cultural shifts, demography, and spatial planning (Bogaerts et al., 2004; Ritsema van Eck, van Dam, de Groot, & de Jong, 2013; van Dam, 2009). Translating these factors to actual trends, a growing population, individualisation and a bigger spread between home and work impact the mobility needs (Bogaerts et al., 2004). Since traffic causes (deadly) accidents, it influences safety. While increasing traffic causes more traffic fatalities worldwide yearly (Evans, 2004), the Dutch government aims to reduce accidents and thereby increase traffic safety (Rijksoverheid, 2016).

To reduce congestion on the roads and to improve traffic safety, the Dutch government took several measures. The Minister of Infrastructure & Environment aims to reduce the deadly fatalities under the 500 per year in 2020 (Ministry of I&E, 2009). Examples of safety measures are constructing more separated cycling lanes, improving junctions and constructing more roundabouts, banning handheld phoning while driving, and campaigns for wearing safety belts and sober driving are showed on all kinds of media (Ministry of I&E, 2009, 2012). With some disturbances, the number of deathly victims reduced from 817 in 2005 to 621 in 2015 (CBS Statline, 2016e). To reduce congestion problems, new roads are constructed, additional lanes are built, and the capacity on big traffic junctions is raised (Ministry of I&E, 2016c). However, it is proved that an increase in road capacity results in an increase in the vehicle miles travelled (VMT) and thereby it does not provide the desired effect of congestion reduction (Noland, 2001). It is even mentioned by Lindsey (2012) that to reduce congestion next to investing in road capacity, road pricing must be introduced. However, an increase in transportation demand increases a country's GDP directly by additional fuel consumption and extra transport services (Han & Fang, 2000). This means that within a government, conflicting interests exists. Next to the capacity measures, measures to reduce the impact on the environment are implemented. Subsidising electrically driven cars and e-bikes intents to result in a modality shift with causing less congestion and fewer emission (Ministry of I&E, 2016a, 2016b).

Nevertheless, globally more and more governments at all levels doubt if investing in infrastructure and transportation technology, which could be out-dated in a few years, will solve the above-mentioned problems (Haboucha, Ishaq, & Shiftan, 2017). A new way to capture those problems is investing in the development of automated vehicles (AVs), also known as self-driving cars. AVs are divided in five categories; from driver assistance (e.g. adaptive cruise control) to full-automation. More information about automated driving can be found in subsection 2.1.1. AVs have the potential to be a technological advancement that could change an individual's view of mobility (Howard & Dai, 2014). Full-automated driving has potential advantages and disadvantages. For example, AVs are able to fundamentally alter transportation systems by reducing the number of fatalities, increasing road capacity, providing mobility to young, elderly and disabled persons, saving fuel, and thereby lowering hazardous emissions (Anderson et al., 2014; Fagnant & Kockelman, 2015). On the other hand, they could increase the road capacity, it has legal issues, and automation systems could malfunction and fail, see subsection 2.1.2. Full-automated vehicles are expected to be commercially available in the Netherlands between 2025 and 2045. The development is, however, highly dependable on external factors like technological development, deadly accidents, and politics (Milakis, Snelder, Arem, Wee, & Correia, 2015).

Before AVs are (widely) available in the Netherlands, it is important to know how users would experience their trips in an AV. The ability to perform activities in an AV is an important facet in the experience of automated driving. The possibility to perform activities in an AV poses very important benefit, and is a determining factor of this study. It is said that when no human attention is required for driving purposes, travel time becomes beneficial if one is able to work or have leisure time during the ride (Jain & Lyons, 2008). Research points out that drivers show more propensity to be involved in in-vehicle activity with increasing level of automation (Jamson, Merat, Carsten, & Lai, 2013). To measure the experience of the automated vehicle users, the Value of Travel Time (VOTT) will be used. The VOTT is used to assign a monetary value to travel time. It implies a monetary value that people are willing to pay to reduce their travel time (WTP). It is expected that due to productivity opportunities the VOTT decreases and thereby that the willingness-to-pay (WTP) to reduce travel time for an AV traveller is lower than for a conventional car traveller (Fagnant & Kockelman, 2015, 2014; Krueger, Rashidi, & Rose, 2016; Yap et al., 2016). A lower VOTT means that the disutility of travel decreases. However, Yap et al. (2016) found in a first study that the VOTT for full-automatically driven vehicle users is higher than for the normal private car users, meaning that one is willing to pay more money to reduce travel time in an AV than in a normal car. A remark is that this study introduced AVs as egress mode. Still, this finding conflicts with other literature and brings us to the following research problem:

There is insufficient knowledge in how people will experience their trips when driving in a full-automated vehicle in relation to driving in a conventional vehicle in the Netherlands.

1.2 RELEVANCE

We conclude that there is insufficient knowledge in how AV users experience their trips compared to conventional car users. This brings us to the relevance of this research, since VOTT is of central interest in transportation research and is a tool to measure trip experience. It is used in assessing transportation investments and it is often used in travel behaviour and traffic assignment models (Tseng & Verhoef, 2008). The VOTT influences the travel behaviour, destination choice, mode choice and so on. Investments in transport(systems) are mostly done to reduce travel time and emissions, and to improve the travel time reliability. The VOTT is used to monetise the travel time savings. In a cost-benefit analysis (CBA) the value of travel time refers to the cost of time spent on transportation. The VOTT is a critical parameter in this transport project appraisal, because most of the times it is the dominant parameter for estimating the monetised benefits of a transportation project (Hensher, 2001a; Jiang & Morikawa, 2004; Mackie, Jara-Diaz, & Fowkes, 2001; Transportation BCA, 2016). In transport project appraisals the VOTT is applied in two ways. On the one side a social value of travel time is used in a CBA for valuing travel time accruing from a transport project. On the other hand VOTTs are used in generalised cost functions for transport demand models (Kouwenhoven et al., 2014).

When deepen into the use in CBA, computing outcomes with wrong VOTTs result in false outcomes; either the project is under- or overestimated. Thus there is, in case of overestimating, less congestion reduction and less emission reduction than calculated, which results in incorrect input for decision-making. This brings us to the aim of this research, which is as follows:

To explore how people in the Netherlands experience a trip in a full-automated vehicle compared to a trip in a conventional car.

1.3 SCOPE

In the problem definition as well as the aim of the research the first two boundaries are set. The first demarcation is the type of AV that will be researched, in this case the privately owned full-automated vehicle. Since less advanced automated vehicles are a combination of human-driving and autonomous-driving, the outcomes of this study could also be used for level 1 to level 4 AVs (for explanation of the levels of automation, see §2.1.1). A level 4 AV drives automatically on motorways, thus the outcome of this study could give a good indication on level 4 AV users driving on the motorway. Besides this argument, automated driving is an unfamiliar mode of transport for humans. It is already challenging to explain precisely what automated driving is. Therefore it is more challenging to explain what level 4 automated driving is in comparison to level 5. Level 5 can be roughly explained as a trip where every driving task is controlled and monitored by a computer, where in level 4 situations occur where the driver is driving the vehicle. Since level 4 is more complicated to understand, and level 4 AV driving requires more complex data gathering, it is chosen that level 5 automated driving is more suitable for this Master thesis.

Secondly, the geographical location is mentioned. It is chosen to delimit the geographical location to the Netherlands, since every country uses its own VOTT indicators (Mouter, 2015). Additional to this argument, data are needed to fulfil this research. Obtaining data in the Netherlands is considered easier than obtaining data from a foreign country.

A third demarcation is the used base alternative for the AV options. It is chosen to measure the VOTT for AVs as main mode, since a first exploratory research has already been conducted for AVs as egress mode, see Yap et al. (2016). The experience of a trip in an AV will be compared to a trip in a privately owned conventional car. Although the Netherlands is a typical bicycle country (CBS, 2015a) this is excluded in this study. The average distance travelled per person per day in the Netherlands was 29.46 km in 2015 (CBS Statline, 2016h). The bicycle is not a common mode for these distances.

Fourthly, shared vehicles are excluded from this study. Since public transport is a shared travel mode, it is excluded from this study as well. By adding public transport like bus, tram and metro (BTM), different access and egress modes must be added too. This results in many alternatives regarding an exploratory study. Any form of car sharing, car-pooling or another form of sharing is not included in this study.

A fifth delineation regards the interior types of the AVs. In this study two forms of interior types are assumed. One can choose either an AV with an office interior or an AV with a leisure interior. The latter interior is design such that one can relax, read a book, watch a movie or interact with family members.

A last important issue to mention is that only one type of trip purpose is assumed. Regarding literature, trip purposes are distinguished in multiple categories. Jiang & Morikawa (2004) mention three categories: commuting trip, business trip, and private trips. Four different kinds of trip purposes are explained by Gupta et al. (2006), which are home-based work, home-based non-work, non-home-based work, and non-home-based non-work. At last, two categories of trip purpose are given by Walker & Ben-Akiva (2002); business trips and non-business trips. Due to simplicity reasons a classical trip purpose will be used. Since 28.3% of the daily travel distances, and 21.0% of the daily travel time is spent on commuting (CBS Statline, 2015a), it is chosen to focus on commuting trips. Other activities that consume a large part of the average distance travelled during a day are 'sport/hobby/hospitality' visits (18.9%) and 'visiting/staying over' visits (19.9%). Two types of commuting trips exist: from home to work and from work to home. In general, the chosen mode of transport in the morning is the one that is used in the afternoon. Furthermore, the morning peak is a common travelling context for transportation research, for example see (Levin & Boyles, 2015; Tseng & Verhoef, 2008). For these reasons, it is chosen to investigate the morning peak trips only: from home to work. To summarise, the most important assumptions and choices are listed below.

- Geographical boundary: the Netherlands;
- Type of AV: private full-automated vehicle;
- Focus exclusively on passenger cars;
- Interior types: office interior and leisure interior;
- Trip purpose: from home to work (morning peak).

1.4 RESEARCH QUESTIONS

This subsection focuses on the research questions. It became clear that the way the VOTT of travellers of automated vehicles compared to travellers of conventional cars will develop is unknown. The main question of this research can therefore be easily derived from the problem statement:

How do full-automated vehicle users experience a trip compared to conventional car users for the trip purpose home-to-work in the Netherlands?

To answer the main question, sub questions are formulated. The sub questions are divided in five categories, which are related to VOTT (in general); to what automated driving is; to the methodology; to data analytics; and to the application of the results. The sub questions are shown and explained below.

1.4.1 Automated driving related

- *What does automated driving mean and what are the different levels of automated driving?*

Having this question answered, it becomes clear what exactly automated driving is and if there are different levels of automated driving. Literature will be used for answering this question.

- *What are the potential (dis)advantages of automated driving?*

This question provides insight in the potential of automated driving. It clarifies what its main benefits and disadvantages are. Having these two questions answered it is easier to decide on what type of automated vehicle to focus on. Literature will be used for answering this question.

1.4.2 VOTT-theory related

- *What is the definition of VOTT?*

By answering this question, it becomes clear what precisely the value of travel time is. Besides having a clear definition of the VOTT it is important to know of what components the VOTT is built. Subsequently, it is useful to explore if different VOTTs exist and why. Literature will be used for answering this question.

- *What is the VOTT that the Netherlands currently uses in its studies and how is it determined?*

This question is formulated to gain knowledge about the current VOTT used in the Netherlands. After obtaining this value and the way it is derived this can be used to validate the findings of this thesis. Literature will be used for answering this question.

1.4.3 Methodology related

- *How can the VOTT be derived from data?*

This question explores the different methods with which the VOTT can be computed. After answering this question it becomes more clear what method to be used for this study. Literature will be used for answering this question.

- *What are the appropriate attributes and attribute levels for the alternatives and what experiment design has to be used?*

The importance of answering this question is in the fact that the survey must obtain useful data to accomplish the aim of this study. For answering this question literature will be used as well as the input of experts.

1.4.4 Data analytics related

- *Are Dutch citizens willing to pay the same amount of money for reducing travel time in an AV as for reducing travel time in a conventional car and what are the differences?*

This sub question is important for answering the main question. This question provides insight as if the VOTT of AV travellers is lower, the same or higher than the VOTT of conventional car travellers. The chosen methodology will be used for answering this question.

<u>Expectation:</u> It is expected that travellers with an AV have a lower willingness-to-pay to reduce their travel time compared to car travellers. The main reason is that people are able to do other activities while driving. This makes travelling less of a burden.

- *Which activity does one prefer to do in an AV; work extra time or save time at the office?*

For simplicity reasons three types of activities can be executed during an AV trip; either one works or one does not work. However, working in an AV can be divided into two components; either you work extra hours thus generating more income and/or more spare days, or instead of working at the office you work in the car, thus you substitute travel time for leisure time. The chosen methodology will be used for answering this question.

<u>Expectation:</u> It is expected that people prefer to start working in the car, so the working time at the office is reduced. This expectation is based on the part-time working climate which is common in the Netherlands, so working extra time for additional income/spare days are not necessary.

- *Do attitudes towards automated driving have a significant influence on the mode choice?*

By answering this questions it becomes clear whether attitudes play a role in the decision-making process. Besides, by knowing which attitudinal factors influence the decision-making AV fabricants and policy-makers could provide the right information to convince potential buyers. The chosen methodology will be used for answering this question.

<u>Expectation:</u> The expectation is that attitudes have an influence. In the study of Yap et al. (2016) it was already shown that attitudinal factors influence the decision-making process.

- *Is a difference in trip experience observable in the case one is driven by a computer or by a human?*

This question is interesting, since it requires a measurement of trip appreciation of users of an AV and of a chauffeur-driven car. By setting up two identical experiments, it is possible to explore if a difference exists between trip experience in an AV and in a chauffeur-driven car. The chosen methodology will be used for answering this question.

<u>Expectation:</u> It is imaginable that a difference in experience is observable. However, in the AV as well as the chauffeur-driven car one is able to work, read, watch a movie and so on. So for the homo economicus it should not make a difference. Still, humans are emotionally creatures, which could make a difference in trip experience possible when being driven by a computer or a human.

- *Which factors influence the preference for automated driving?*

This last sub question aims at gaining insights in what social-demographic variables are more connected to a preference for automated driving. This question could provide information regarding what kind of individuals are most suitable for using automated vehicles. The chosen methodology and literature will be used for answering this question.

<u>Expectation:</u> It is expected that age, daily occupations and attitudes play a significant role in decision-making. Young people are more used to computers, while older people are more sceptic about automation and computers. Furthermore it is expected that working people and students have a preference for AVs, while retirees prefer the conventional car. Because people can now work in a car, which could reduce the time at the office and could increase the time at home, it is expected that employees/employers prefer an AV. Students are expected to choose an AV option sooner, because of their age.

1.5 THESIS OUTLINE & DESIGN OF RESEARCH

Chapter 2 contains an elaborated literature review about the two main subjects 'automated driving' and 'value of travel time'. It also includes descriptions of three other VOTT studies in the Netherlands. In these reviews the three studies are explained in four parts: instrument, sample, model, and results. In chapter 3 an explanation is provided about what method(s) can be used and will be used. After the argumentation why these methods are required for this study the requirements of the survey are given in chapter 4. Then, in chapter 5 the construction of the final survey is explained. Chapter 6 shows the descriptive statistics of the samples, whereas chapter 7 shows the results of the latent variable model (exploratory factor analysis) and the discrete choice models. This chapter contains a discussion of the results as well. At last, chapter 8 includes the policy implications, the answer to the sub and main question, conclusions, recommendations and a personal reflection on the graduating process.

Figure 1.2 shows a schematic overview of the design of the research. The first phase of this thesis contains an elaborated literature study. The literature provides insights in the concepts automated driving and value of travel time. The collected literature provided further understanding on what has been done in the field of automated driving and VOTT. At the end of the literature study knowledge gaps were found, research questions are composed, and a methodology to answer the research questions has been proposed. The second step was to dissect the method. Using the literature it was concluded that Stated-Preference (SP) experiments were required in combination with an exploratory factor analysis (EFA). The last step of phase two was to decide which attributes should be included in the survey and to design the SP experiments. It was decided to use an efficient design to construct the SP experiments. In the third phase a prior-estimation study has been set up and distributed to estimate priors. These priors are eventually used in the efficient designs of the final SP experiments. After estimating the priors the final surveys were distributed to two online panels in the Netherlands in phase four. With the collected data of the final surveys the exploratory factor analysis is conducted. The software package SPSS (IBM, n.d.) is used for the EFA. After the EFA, different discrete choice models were estimated with the software tool BIOGEME (Bierlaire, 2003). The last step in phase four is to analyse the data. Finally, in phase five the main research question is answered, and clear conclusions and recommendations are given.

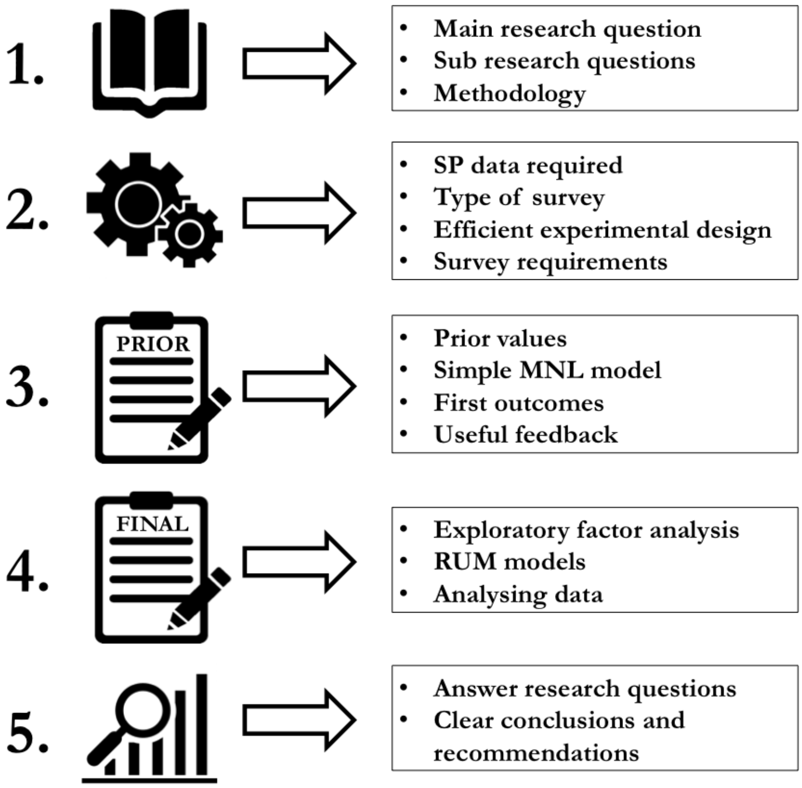

Figure 1.2: Design of research. Symbols used from: (Free incons png, 2016; Graphic Resources LLC, 2017; IconsDB, 2017).

This chapter contained five parts. In the first part the subject of this thesis was explained. Then, the relevance of this research was described and the aim of the research was defined. In this part we learned that there is insufficient knowledge in how people will experience a trip in an AV compared to a trip in a conventional car. Subsequently, the scope of the research was determined followed up by defining the main research question '*How do full-automated vehicle users experience their trip compared to conventional car users for the trip purpose home-to-work in the Netherlands?*'. After defining the main research question, the sub questions were described. The last part showed the thesis outline and the design of the research.

2 LITERATURE STUDY

This section is divided in four parts. In the first part it is described what automated driving is. Subsection 2.2 explains what the value of travel time (savings) means. The value of travel time reliability is shortly discussed in this subsection as well. Paragraph 2.3 provides insights into recent VOTT studies in the Netherlands. In the last subsection (§2.4) studies about automated driving preferences are briefly discussed.

2.1 WHAT IS AUTOMATED DRIVING?

The introducing section of this thesis made clear that this research is about full-automated driving and the experience of its users measured through the value of travel time. However, what exactly is automated driving? This subsection provides an answer on what automated driving is, what its (dis)advantages are, and it will provide examples of current AV projects.

2.1.1 DEFINING AUTOMATED DRIVING

Automation finds its origin in the Greek word *automatos*, meaning acting by itself/spontaneously. Before defining what automated driving is, it has to be clear what automation is. In the *Handbook of Automation* Nof (2009) defines automation as follows: *'Automation, in general, implies operating or acting, or self-regulating, independently, without human intervention'*. Most important part of this definition is 'without human intervention', which implies that an automated system must have some feedback mechanism that controls the functionality of the system. Four main principles of automation confirm this: mechanisation, process continuity, automatic control, and automation rationalisation. Where mechanisation implies as the application to perform work, process continuity guarantees the workflow, and the control mechanism provides adaptions due to feedback loops. The rationalisation tests the analysis, understanding and evaluation of the automation solution (Nof, 2009). Table 2.1 gives an interpretation of the four automation principles for automated driving.

Table 2.1: Automation principles translated to automated driving.

Automation principles	*Automated driving*
Mechanisation	System takes over human tasks of driving. (e.g. steering, accelerating, braking)
Process continuity	System makes sure that mechanisation tasks are executed in a continuous way. (e.g. continuously driving 100 km/h on a 100 km/h road)
Automatic control	System monitors and reacts to the (changing) environment. (e.g. braking when vehicle in front brakes)
Automation rationalisation	System brings users of an AV from A to B in a safe and sustainable manner.

After applying the automation principles to automated driving a clear definition of automated driving should be obtained. It is hard, however, to come up with one clear definition for automated driving, since it depends on the extent of automation. For example, is a vehicle completely driven by a computer or is automation used as support such as adaptive cruise control (ACC) or automatic parking?

Currently six levels of automation are defined in the literature, where level 0 is a vehicle without any form of automation. These levels are driver assistance (level 1), partial driving automation (level 2), conditional driving automation (level 3), high driving automation (level 4), and full driving automation (level 5) (SAE International, 2016). Level 0 up to and including 2 can be seen as 'human driver monitors the driving environment'; while the upper three levels of automation are noted as 'the automated driving system monitors the driving environment' (Gasser & Westhoff, 2012). The extent to which a driver controls and intervenes becomes less in every step of the automation. The level of automation depends on its performance on four criteria: sustained lateral and longitudinal vehicle motion control (SLL), object and event detection and response (OEDR), dynamic driving task fall back (DDT fall back) and the operational design domain (ODD). Examples of longitudinal control in vehicles are the adaptive cruise control (ACC) and lane departure warnings (LPW) (Fagnant & Kockelman, 2015; Luettel, Himmelsbach, & Wuensche, 2012). The normal DDT is a combination of SLL and OEDR (SAE International, 2016).

Table 2.2: Levels of automation, where 'system' refers to automated driving system (ADS) (SAE International, 2016).

Level of automation	*SLL*	*OEDR*	*DDT fall back*	*ODD*
No driving automation	Driver	Driver	Driver	n/a
Driver assistance	Driver and system	Driver	Driver	Limited
Partial driving automation	System	Driver	Driver	Limited
Conditional driving automation	System	System	Fall back-ready user	Limited
High driving automation	System	System	System	Limited
Full driving automation	System	System	System	Unlimited

Since the focus is on full-automated driving, it is important to understand the difference between level 4 and level 5 automated driving. The difference is found in the possibilities to move in the ODD. An ODD includes geographical, roadway, environmental, traffic, speed and/or temporal limitations. Besides, an ODD may include one or more vehicle operations with specific DDT requirements like motorway merging or low-speed traffic jam driving (SAE International, 2016). We can conclude that full-automated vehicles have an unlimited ODD and are able to cope with every traffic situation, while the high-automated vehicles have limitations.

2.1.2 POTENTIAL (DIS)ADVANTAGES OF AUTOMATED DRIVING

The previous section described what automated driving is and what the differences are between the different levels of automated driving. This subsection aims at revealing the main advantages and disadvantages of the AV application.

AVs are able to fundamentally alter transportation systems by means of multiple effects. AVs aim to achieve all kinds of efficiency benefits like travel time efficiency, a reduction of congestion, and resource efficiency (Haboucha et al., 2017). The concept of platooning, where vehicles travel together actively in formation (Bergenhem et al., 2012), enables the optimisation of traffic flow management, increases the road capacity, and increases the aerodynamic drag resulting in even more fuel efficiency and less emissions (Beiker, 2014; Haboucha et al., 2017). A higher road capacity and smoother traffic flow related to less congestion and thus to less stop-and-go driving. This has a positive effect on the fuel consumption and emissions (Anderson et al., 2014; Beiker, 2014; Fagnant & Kockelman, 2015; Howard & Dai, 2014). The increase in road capacity and the decrease in congestion produces more travel time savings for road users (Howard & Dai, 2014).

Besides time and environmental benefits, full-automated AVs have the potential to increase mobility since, in theory people, do not need a driving license to operate these vehicles (Anderson et al., 2014; Fagnant & Kockelman, 2015; Howard & Dai, 2014). So, AVs brings more mobility to elderly people, disabled people or young people.

Furthermore, AVs have the potential to obtain safety improvements (Anderson et al., 2014; Fagnant & Kockelman, 2015). In light traffic, high levels of automation improve road safety, and on highways drivers intend to change less from driving lane. Also during a traffic jam, there is a tendency to remain in a central driving lane when driving with an automation application. It appears that drivers seem unconcerned that this lane choice results in higher travel times (Jamson et al., 2013). In the USA 93% of the crashes are due to human error (NHTSA, 2008) and the use of AVs could reduce this theoretically to zero per cent (Fagnant & Kockelman, 2015).

However, while most driving situations are potentially easy to understand for an AV, it seems arduous to design a system in which AVs could manoeuvre always safely (Campbell, Egerstedt, How, & Murray, 2010). For example, the recognition of animals and other objects on the road is harder for AVs than for human drivers (Dalal & Triggs, 2005; Farhadi, Endres, Hoiem, & Forsyth, 2009). This is a big disadvantage, because in residential areas or other crowded places it results in a low velocity. Nowadays, individuals recognise that AVs could reduce fatalities, however they are still sceptic about automation issues such as system failure, system breeching, and empty driven cars (Bansal, Kockelman, & Singh, 2016; Casley, Jardim, & Quartulli, 2013; Fraedrich & Lenz, 2014; Howard & Dai, 2014; KPMG, 2013; Schoettle & Sivak, 2014). So, to achieve the theoretical advantages, a lot of developments still have to be done.

Cost and safety issues mostly make individuals hesitant in accepting and using new technologies. It is not clear whether automated driving increases or decreases the travel costs. It is possible that a new technology is more expensive than normal car driving. However, the technology is also able to reduce fuel and insurance costs (Casley et al., 2013; Fraedrich & Lenz, 2014; Howard & Dai, 2014; Kyriakidis, Happee, & De Winter, 2015; Schoettle & Sivak, 2014). However, the average rate of return is not yet known.

Automated driving could affect a travel behavioural change. An AV is able to subtract travellers from other modes like the train and thus creating more traffic on the road, which will increase the mobility of individuals. An increase in mobility brings welfare, however generating more road-travel demand has negative environmental consequences. An increase in mobility demand higher a road capacity. A higher travel demand results in more vehicle miles travelled (VMT) (Fagnant & Kockelman, 2015, 2014). In the case of a lack of demand-management it is estimated that in the United States the VMT increases resulting in negative environmental consequences (Gupta et al., 2006; Litman, 2016). Automated driving on itself has a causal relationship with the VMT. For example, empty cars could drive themselves to cheaper parking spaces outside the city, which result in more kilometres. More driven kilometres requires more fuel usage and more pollution. The ability of self-driving could result in redevelopment of land-use. In this example, fewer parking space are required at denser places, which enables redevelopment of high-valued areas. Literature is not clear whether the increase in road capacity is higher than the increase in travel demand.

A disadvantage of AVs is that people could lose their job. Taxi drivers become unnecessary if shared AVs are around, bus drivers become unnecessary when the public transport will be automated.

Many ethical, legal and liability issues still require an answer (Howard & Dai, 2014; KPMG, 2013; Schoettle & Sivak, 2014). A prominent legal issue tries to find answers on the determination of fault and liability in the case an AV is involved in an accident (Beiker, 2014). A question such as 'who is responsible when an empty AV causes a deathly accident?' needs an answer and consensus. This makes clear that new legislation is required before allowing AVs on the road.

Since full-automated vehicles have the possibility to be comfortably equipped (Fraedrich & Lenz, 2014), and do not need human attention on the road (SAE International, 2016), there is the possibility to perform other activities while driving. For example, Jain & Lyons (2008) mention that travel time is beneficial if people are able to perform activities such as working or phoning family and friends. Research points out that drivers show more propensity to be involved in in-vehicle activity with increasing level of automation (Jamson et al., 2013). Conducting other activities while driving was found to be one of the biggest advantages of AVs (König & Neumayr, 2017). The ability to perform other activities while driving is a crucial assumption in this research. It is expected that, due to the possibility of doing other activities, the VOTT of AV users will be lower than the VOTT of conventional car users.

To give a clear overview, the potential advantages and disadvantages described in this subsection are shown in the table below. Some effects are written down as potential advantages and as potential disadvantage, since literature is not clear about the precise effects.

Table 2.3: Summary of potential advantages and disadvantages of automated driving.

	Potential advantages	**Potential disadvantages**
Society's perspective	Time savings Less congestion Fuel efficiency and less pollution Increase in mobility Improved traffic safety Redevelopment of land-use Higher road capacity	More demand in road capacity Increase in VMT Technology failures Legal and liability issues Hard to realise a system where AVs could drive always safely More congestion
Traveller's perspective	Lower operating costs Time savings Increase in mobility **Able to perform activities while driving**	Higher purchase costs Losing jobs (e.g. taxi driver)

2.1.3 AUTOMATED DRIVING TODAY

Many examples of automated driving exist. Automated driving varies from adaptive cruise control to fully computer driven cars. This paragraph gives three examples to bring this research more to reality. Two well-known examples of automated vehicle are highlighted: Google's self-driving car and Tesla's Autopilot. The chapter ends by drawing a parallel between AVs and a car with a chauffeur.

2.1.3.1 GOOGLE'S SELF-DRIVING CAR

The first example of full-automated driving is the Google self-driving car. In 2009, Google started the self-driving car project. Google aims to provide a technology that is able to get everyone around easily and safely, regardless of his or her ability to drive. The Google self-driving cars are equipped with sensors, software and maps to determine exactly where it is driving. The core of Google's AV is built around four main questions, which are:

- Where am I?
- What is around me?
- What will happen next?
- What should I do?

Software and smart algorithms are used to predict what surrounding objects are going to do, to stay in the correct driving lane, and to adapt on unexpected changes. Pilots have driven for more than two million miles and are currently on the streets in cities in the USA. The Google-self-driving car is still in a testing phase (Google, 2016).

2.1.3.2 TESLA'S AUTOPILOT

Second example is the self-driving car by Tesla. Tesla developed software and equipment for the *Model S, Model X,* and *Model 3* to be able to drive completely automated using eight cameras. With the Tesla Autopilot tool, cars are able to stay on its driving lane, to change lanes without human interference, to drive on and off ramps, to park themselves, and to drive in and out of the garage. The system is designed for short- and long-haul distances. The complete autopilot software claimed to be able to drive the car without human interference on all kinds of roads, crossings, roundabouts and stop signs (Tesla, 2016). However, in practise it is not yet a substitute for the human driving, but more a complementary tool (Taub, 2016).

Tesla has tested the Autopilot tool for more than 130 million miles. About every 60 million miles a fatality occurs worldwide with a Tesla using the Autopilot software (Golson, 2016), while on average in the USA every 92.6 miles a fatality occurs (NHTSA, 2015). It is not as safe as manual driving Tesla is improving it self-driving system continuously, however deadly accidents still occur. Last fatal accident was in Florida when the Autopilot software as well as the driver did not recognise a trailer on the road (Golson, 2016). Cases where the Autopilot recognised accidents and braked on time are known as well (NOS, 2016).

2.1.3.3 CAR WITH CHAUFFEUR

To draw a parallel with automated driving and current transportation modalities an example will be provided in this subsection. The best way to describe a ride with a full-automated vehicle is to imagine a ride in a car with a driver, such as a taxi ride, Mercedes-Maybach ride or a limousine ride. One sits at the back of the car and is able to do all kind of activities in the car without paying any attention to the traffic. The user got driven from A to B without driving the car him- or herself. A big difference between a ride in an AV and a taxi/limousine are the costs. In the AV you do not have to pay for the driver. So, to bring automated driving to reality, one should imagine that one has:

- A car always available;
- A free driver always available, and;
- Activities to do.

2.2 WHAT IS VALUE OF TRAVEL TIME?

This research has two main cornerstones: automated driving and the value of travel time. In the previous section it was clearly described what automated driving is, what its benefits and limitations are, and what the current state of automated driving is. This section has the focus on the second cornerstone. It deepens into what the VOTT is, how it can be computed, and its applications.

2.2.1 HISTORY OF THE VALUE OF TRAVEL TIME

To describe what the VOTT is, the theory of time allocation by Becker is used. Becker (1965) says that one does not gain utility directly from the consumption of goods, but from the final commodities that require goods and time as input. For example, not the groceries one buys in the store gain utility, but the meal you cooked with it. In his theory time is converted into money by allocating more time to work instead of non-work activities. This brought the first definition of value of time: that consumption has a time cost of not earning money. In simple words, the value of time was equal to the hourly salary (wage rate).

A few years later a distinction has been made between non-work activities. In the previous definition VOTT is equal to the value of non-working time. Thus travel time on itself was added in the utility function since travelling itself creates utility (Oort, 1969). If travel time is reduced, the time spent to work or leisure activities increases. This changed the perception of VOTT, because it is not only the value of non-working time, but it should include the direct perception of travel time too. With this perception, DeSerpa (1971) defined three value of times:

- Value of time as resource (VTR): value of extending the time period
  - Ratio of marginal utility of the available time (μ) and marginal utility of income (λ): μ/λ
- Value of time as commodity (VTC): value of time allocated to a certain activity, and;
  - Ratio of marginal utility of time spent in an activity i ($\partial\mu/\partial t_i$) and marginal utility of income (λ): $(\partial\mu/\partial t_i)/\lambda$
- Value of time savings (VTS): value of reducing time required to spend in an activity
  - Ratio of the marginal utility of time savings in an activity i (k_i) and the marginal utility of income (λ): k_i/λ

DeSerpa (1971) showed that the VTS in an activity is equal to VTR minus VTC. In the case of transportation it is only equal to VTR if travel time produces no utilities. De Donnea (1972) draws the same conclusion: value of travel time savings is the VTR minus the value of satisfaction resulting from the circumstances.

This value of travel time savings has two shortcomings: the variation in the consumption of goods due to the substitution of travel time for other activities, and the possibility of rescheduling activities (Mackie et al., 2001). Firstly, the substitution of travel time for other activities results in a change in consumption patterns. Secondly, different VOTTs exist when one arrives on time, too early or too late at an activity. The departure time influences the travel time, travel costs, and utility (Small, 1982; Vickrey, 1969). This relationship affects the reliability of travel, which is explained in §2.2.3. A new value of travel time savings has arisen: VTR minus VTC plus the value of cost savings due to time savings (Jiang & Morikawa, 2004). The formulation of DeSerpa (1971) is, however, still presently accepted (Mackie et al., 2001).

For synthesis, travel time reduction matters to an individual, because a decrease in total travel creates more time for other activities. This realises a change in the consumption pattern, and a rescheduling could take place. If paid work increases, the consumption pattern of individuals changes as well. Thus, there is a willingness to pay for a reduction in travel time if the sum of the abovementioned determinants is positive (Mackie et al., 2001). This brings us to the neo-classic definition for the value of travel time savings (VOTT): *the willingness to pay for a unit-travel time saving (WTP)*. This value of travel time savings varies with socio-economic and travel environments (e.g. Ettema & Verschuren, 2007; Fosgerau & Engelson, 2011; Hensher, 2001; Jiang & Morikawa, 2004). For example, travel time of public transport can be divided into in-vehicle time, walking time, and waiting time, each with its own value of time (Carrion & Levinson, 2012). In the Netherlands it is measured that waiting time for bus/tram/metro (BMT) is valued 2.2 times more negatively than in-vehicle time (Bovy & Hoogendoorn-Lanser, 2005). The valuation of walking time was measured about 1.6 times more negatively than in-vehicle time (Arentze & Molin, 2013; Bovy & Hoogendoorn-Lanser, 2005; Yap et al., 2016). Wardman (2004) concluded that it is accepted that walking time is valued twice the in-vehicle time of PT and that waiting time is valued 2.5 times the in-vehicle time of PT.

2.2.2 METHODS TO DERIVE THE VALUE OF TRAVEL TIME

The value of travel time savings (VOTT) is defined as the willingness to pay for one unit of travel time saving (WTP), so how much money is an individual willing to pay to reduce their travel time by one time unit. But the question is '*How can the VOTT be derived from data?*'.

The VOTT can be influenced by and differentiated on many dimensions. Six major influences are defined: time at which the journey is made, characteristics of the journey, journey length, journey purpose, mode of travel, and the size of the time saving (Mackie et al., 2001). A differentiated VOTT between modes, purpose and journey length improves the quality of CBAs. Countries such as the UK and the Netherlands differentiate the VOTT on different aspects. However in CBAs governmental parties use one VOTT, since politicians do not accept this variation for political-philosophical reasons (Mouter, 2015).

Breidert, Hahsler & Reutterer (2006) mention that seven methods exists to determine the VOTT, which are visualised in Figure 2.1.

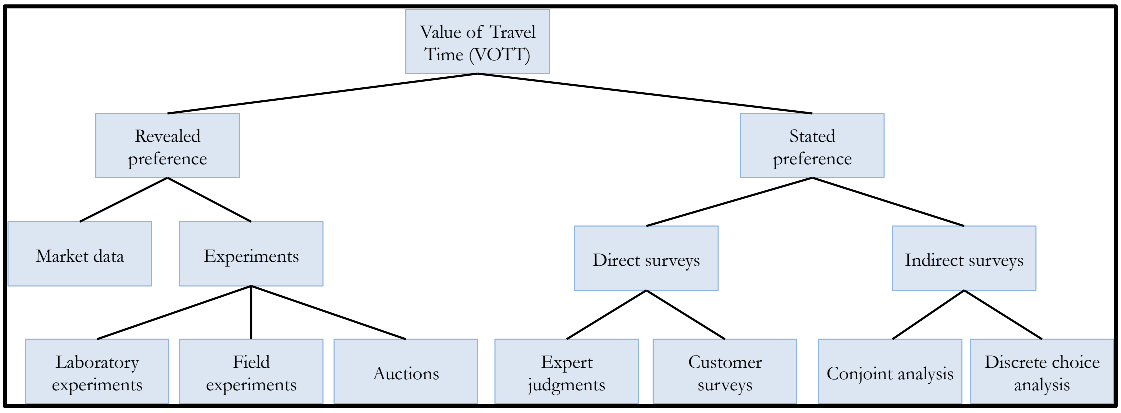

Figure 2.1: Classification framework for methods to measure VOTT (Breidert et al., 2006).

One of this methods is the use of discrete utility choice models. In a discrete utility model it is assumed that an individual always chooses the alternative that generates the most utility depending on the given attributes (Walker & Ben-Akiva, 2002). The discrete utility model infers the VOTT by the negative of the marginal rate of substitution (MRS) between travel time and travel costs, see below (Dekker, 2014).

Equation 1

$$\mathrm{VOTT^{RUM}} = -\mathrm{MRS} = \frac{\partial \mathrm{E}\left(\max\{\mathrm{U_j}, \forall \mathrm{j} \in \mathrm{D}\}\right)/\,\partial \mathrm{T_i}}{\partial \mathrm{E}\left(\max\{\mathrm{U_j}, \forall \mathrm{j} \in \mathrm{D}\}\right)/\,\partial \mathrm{C_i}} = \frac{\partial \mathrm{V_i}/\,\partial \mathrm{T_i}}{\partial \mathrm{V_i}/\,\partial \mathrm{C_i}}$$

Where U_j is the utility of all J alternatives in choice set D, and $VOTT^{RUM}$ is the value of travel time for linear-additive random utility maximisation models. In most studies this is the ratio of the travel time and travel costs parameters β_{TT}/β_{TC} if the parameters are linear. This is called the subjective VOTT. Mackie et al. (2001) confirm this VOTT determination.

Next to utility-based discrete choice models, regret-based discrete choice models (RRM) exist. Regret-based discrete choice models assume that respondents choose the alternative that generates least regret (Chorus, 2010). To compute the VOTT with RRM models, the following formula can be used (Chorus, 2012):

Equation 2

$$VOTT^{RRM} = \frac{\partial R_i / \partial T_i}{\partial R_i / \partial C_i} = \frac{\theta_T}{\theta_C} \frac{\sum_{j \neq i} \exp\left(\theta_T (T_j - T_i)\right) / 1 + \exp\left(\theta_T (T_j - T_i)\right)}{\sum_{j \neq i} \exp\left(\theta_C (C_j - C_i)\right) / 1 + \exp\left(\theta_C (C_j - C_i)\right)}$$

Where T_j and C_j represents travel time and travel costs respectively in alternative j, and T_i and C_i are the same values for alternative i.. The symbol θ represents the difference in regret between two alternatives based on a certain attribute. Chorus (2012) discusses that only the ratio of the time and costs parameters does not provide a correct VOTT in this matter Dekker (2014) made the VOTT of the RRM more complete, but also more complex in his study.

The other six methods to derive the VOTT by Breidert et al. (2006) are market data analysis, laboratory experiments, field experiments, auctions, expert judgements, customer surveys, and conjoint analysis.

To determine the WTP via a laboratory experiment an individual is given a certain amount of money and is asked to spend it on a specific selection of goods. This method is used in sales industries like clothing shops (Breidert et al., 2006). Field experiments are laboratory experiments executed in the real world. Respondents are not always aware that they participate in the experiment. A special application of experiments is an auction (Breidert et al., 2006). An auction is, however, mostly used for scarce, unique and high-valued goods. Using historical market data that does not have sufficient price variations brings problems when estimating WTP values (Breidert et al., 2006). Sattler & Nitschke (2003) argue that using market data for WTP estimation is infeasible. Since no tangible market exists for buying travel time, these methods are not suitable for this study (Transportation BCA, 2016).

During expert judgements and customer surveys one is asked to assign a price to a good directly. Expert judgements are mostly useful in a market environment with few customers. With the obtained data from experts, it is possible to come up with a WTP estimate. This method is, however, a poor method for WTP estimation due to low validity (Breidert et al., 2006). The customer survey method has issues as well. Firstly, respondents could not assign their real WTP, because of prestige (too high) or consumer collaboration behaviour (Nessim & Dodge, 1995). And secondly, VOTT value of travel time for automated driving. (Brown, Champ, Bishop, & McCollum, 1996).

Besides discrete choice modelling, a last possible method for calculating the VOTT is the conjoint analysis. Conjoint analysis is defined as the decomposition into part-worth utilities or values of a set of individual assessments of, or discrete choices from, a designed set of multi-attribute alternatives (Louviere, 1988). Respondents have to rate alternatives on a rating scale with which a regression analysis is conducted (Molin, 2015a). To determine the WTP from conjoint analysis, part-worth utilities are used. The difference in price is compared to the difference in utility on that attribute. It is discouraged to use this method, because it could result in misleading values and problems occur when utility is not linearly related to price (Orme, 2010). Furthermore, this analysis is hardly used in transportation anymore (Molin, 2015a).

2.2.3 VALUE OF TRAVEL TIME RELIABILITY

A application that is applied more often is the value of travel time reliability (VOR). Mackie et al. (2001) mentioned two shortcomings in the VOTT measurement. The VOR is related to the shortcoming regarding rescheduling activities. Vickrey (1969) explains that arriving too early or too late at the destination due to congestion involves different VOTTs. The VOR indicates the value travellers place on the reliability of estimated travel time and measures the willingness to pay to reduce the variability of travel time (Brownstone & Small, 2005).

Unpredictable variations have a direct link with uncertainty in travel time. Five categories of causes of uncertainty in travel time are mentioned in the literature. These categories are:

- Variation between seasons and days of the week (Wong & Sussman, 1973);
- Variation because of weather and crashes or incidents on the network (Wong & Sussman, 1973);
- Variations attributed to each traveller's perception (Wong & Sussman, 1973);
- Link flow variations (Nicholson & Du, 1997), and;
- Capacity variations (Nicholson & Du, 1997).

Higher travel time variability leads to higher travel time unreliability. Two main approaches are developed to determine the VOR: the centrality-dispersion (or mean-variance) model and the scheduling model. The former method is more commonly used, since it requires only knowledge of day-to-day travel time distributions whereas scheduling models need preferred arrival times as well. The utility (V) function makes use of the expected travel time (μ_T) and the travel time variability (σ_T), where the objective is to minimise both components (Carrion & Levinson, 2012).

Equation 3

$$V = \beta_1 \mu_T + \beta_2 \sigma_T + \beta_3 C$$

Where C represents a cost-oriented attribute. The VOTT is then calculated the same way as showed in the RUM method. Calculating the VOR has a similar form.

Equation 4

$$VOR = \frac{\partial V / \partial \sigma_T}{\partial V / \partial C}$$

The reliability ratio is the ratio of the VOR and the VOTT (Carrion & Levinson, 2012; Kouwenhoven et al., 2014). The VOR could be of importance for full-automated vehicle users if the VOTT decreases. This means that less disutility is experienced when travelling in an AV. Annema (2017) claims that the importance of reliability could increase by a decrease of the VOTT. Nonetheless, this study is an exploratory study to the VOTT for full-automated vehicle users, so the VOR is excluded from this study and must be researched in another study.

2.3 VOTT STUDIES IN THE NETHERLANDS

This paragraph contains descriptions of existing VOTT studies in the Netherlands. The purpose of describing other studies is to get an indication whether it is possible to compare the results of this study with the results of other studies. Three studies are discussed, which are Arentze & Molin (2013), Kouwenhoven et al. (2014), and Yap et al. (2016). Per study a description is given about the used instrument for gathering the data, the sample, the model(s) used, and the results.

2.3.1 REVIEW 'CHOICE BEHAVIOUR IN A MULTIMODAL NETWORK SETTING'

Existing choice behaviour studies had the focus on either public or private modes in isolation. The aim of this study is to provide an experiment where the full range of choice options in multimodal network settings on a high level of detail concerning the trip stages, attributes, and trip distances is considered (Arentze & Molin, 2013).

2.3.1.1 INSTRUMENT

This study used a Stated-Preference approach with four different choice experiments. The four experiments differ from each other on the range context and the alternatives.

Table 2.4: Four experiments by Arentze & Molin (2013).

	Experiment 1	*Experiment 2*	*Experiment 3*	*Experiment 4**
Range	5 km	20 km	20 km	65 km
Alternatives	Bicycle, car, and (Bus, tram, local train)	Car, (bus, local train, intercity train), and (car + bus, train, tram)	Bus, local train, and intercity train	Train, train, and train
Choice sets constructed	27	27	45	45

**Alternatives of experiment four are differentiated by access mode and egress mode, see Arentze & Molin (2013).*

Efficient designs were used to construct the choice sets per experiment. On forehand, a prior study had been executed to determine priors that are used in the efficient designs of the final experiments. The respondents were recruited from a large national panel in the Netherlands.

2.3.1.2 SAMPLE

Totally 2,746 respondents completed one of the four surveys. The number of respondents per experiment was 601 (exp 1), 547 (exp 2), 711 (exp 3) and 887 (exp 4). Each respondent had to fill in nine choice sets, resulting in 24,714 observations.

The socio-demographic characteristics of the experiments are compared with each other as well. The first two experiments are identified as multimodal (MM) choice experiments, where the other two experiments are described as public transport (PT) choice experiments. All groups in in terms of age, education, work status, and household composition have approximately equal shares for the MM and PT experiments. No information is given whether the sample is represents the Dutch population well.

2.3.1.3 MODEL

Discrete choice models were used to analyse the SP data. Scaled error-component ML models were applied. The advantage of this methodology is that it is possible to estimate valuations of time, costs and service-quality attributes on a relatively high level of detail concerning modes and trip stages. The final proposed model specification of this study is as follows:

Equation 5

$$U_i = \mu_i V_i + \eta + \varepsilon$$

Where V is the structural-utility, η is the shared error component between alternatives, and ε represents independent and identically distributed (i.d.d.) error components, subscript i identifies the experiment ($i \in$ exp1, exp2, exp3, exp4), and μ's are scale parameters to be estimated.

2.3.1.4 RESULTS

The VOTT results are shown in Table 2.5. Arentze & Molin (2013) mention that the VOTT estimates are in line with findings of other studies in this research area. A complexity in this study was that the estimates of the value of a euro differs depending on type of expenditure. To cope with this, the ticket costs for public transport were used as best indicator to calculate the VOTT ratios for each mode of transport.

Table 2.5: Values of travel time (in €/h/person) for car driver and train user (Arentze & Molin, 2013).

	Car	*Train*
Long range	12.42	14.16
Short range	22.74	17.40
Average	17.58	15.78

The relevant estimated parameters of this study are shown in the next table.

Table 2.6: Relevant parameter estimates (Arentze & Molin, 2013).

	T_main_car	*T_main_car_short*	*T_egress_walk*	*C_fuel*	*C_ticket*
Value	-0.079	-0.036	-0.101	-0.098	-0.207

2.3.2 REVIEW 'DETERMINE THE OFFICAL VOTT INDICATORS FOR DUTCH CBAS'

The objective of this study was to update the official CBA VOTTs for both passenger and freight transport in the Netherlands and to deliver VORs. Only the results of passenger transport are discussed below.

2.3.2.1 INSTRUMENT

Web-based SP interviews were carried out in 2009 and 2011 to gather data among travellers. The questionnaire consists mainly of three SP experiments. The choice situations in all SP experiments are within-mode choices. So, given a certain mode, each choice set consists of two generic alternatives and the respondent was asked to choose the preferred option. Experiment 2b is similar to experiment 2a, but without the variation in the most likely arrival time. An overview of the experiments is shown in Table 2.7, further information regarding the experiments can be found in Kouwenhoven et al. (2014).

Table 2.7: Three experiments by Kouwenhoven et al. (2014).*

	Experiment 1	*Experiment 2a*	*Experiment 2b*
Attributes in experiment	Usual transport time, transport costs	Usual transport time, transport costs, reliability, five possible transport times, departure time	Usual transport time, transport costs, reliability, five possible transport times, departure time
Choice sets	6	6	7

**Except recreational navigation*

So-called Bradley designs are used to construct the SP experiments. Bradley designs are mostly similar to orthogonal designs, however it circumvents with dominant alternatives. Two datasets were collected, one using online panels and one using interviews at petrol stations, parking garages, airports etcetera.

2.3.2.2 SAMPLE

In total 4,315 interviews were used of the Internet survey and 1,144 interviews of the en-route recruitment survey were used. The number of interviews represented 95,172 observations. The survey was made representative for the Dutch population. All trips were divided in five socio-demographic variables and trip variables. In this survey the distribution of the trips over the seven variables were different from the Dutch population. An iterative proportional fitting method has been applied to calculate new weights such that the weighted distributions for the seven variables match the Dutch population.

2.3.2.3 MODEL

Four types of discrete choice models were estimated. These models are MNL mean-dispersion models, advanced MNL mean-dispersion models, advanced MNL mean-dispersion models with socio-economic interaction terms, and latent class mean-dispersion models. The latter method is used to calculate the new VOTTs. This method accounts for unobserved differences between respondents in the VOTT and for repeated measurements/panel effects. To optimise the number of classes per estimate the Bayesian Information Criterion was used.

2.3.2.4 RESULTS

Table 2.8 shows the determined VOTTs. The VOTTs found from the Internet panel survey were substantially lower than the VOTTs found from the en-route recruitment survey.

A big difference between Kouwenhoven et al. (2014) and Arentze & Molin (2013) is that the latter made a distinction between distance ranges. Another difference is that the former study aims to find VORs next to the VOTTs and the study of Arentze & Molin (2013) does not.

Table 2.8: New values of time (in 2010 €/h/person, including VAT) for car driver, train, bus/tram/metro, air and recreational navigation (Kouwenhoven et al., 2014).

	Car	*Train*	*BTM*	*All surface modes*	*Air*	*Recr. Navigation*
Commute	9.25	11.50	7.75	9.75		
Business employee	12.75	15.50	10.50	13.50	85.75	
Business employer	13.50	4.25	8.50	10.50	-	
Business	26.25	19.75	19.00	24.00	85.75	
Other	7.50	7.00	6.00	7.00	47.00	8.25
All purposes	9.00	9.25	6.75	8.75	51.75	8.25

Note: all values are rounded on €0.25 values.

2.3.3 REVIEW ‘ CHOICE BEHAVIOUR WITH AV AS EGRESS MODE’

The main objective of the study by Yap et al. (2016) was to position AVs in the transportation market and understand the sensitivity of travellers towards some of their attributes, focusing particularly on the use of AVs as egress mode of train trips.

2.3.3.1 INSTRUMENT

Yap et al. (2016) used a SP study with choice sets including five alternatives. Each choice set proposed the same context, which was a trip from home to a certain activity such as work, study or a business meeting. Table 2.9 provides an overview of the alternatives per choice set.

Table 2.9: Alternatives per choice set by Yap et al. (2016)

Alternative 1	*Alternative 2*	*Alternative 3*	*Alternative 4*	*Alternative 5*
Train + BMT	Train + bike	Train + AV – drive yourself	Train + AV – full-automation	Car
1st class or 2nd class	1st class or 2nd class	1st class or 2nd class	1st class or 2nd class	1st class or 2nd class

D-efficient designs were used to construct 12 choice tasks. Each respondent had to answer six choice sets. The priors for the efficient design were drawn from a uniform distribution by quasi-random Monte Carlo draws using Halton sequences to approximate Bayesian efficiency. Besides SP choice tasks 23 statements are showed to each respondent, which they have to rate from totally agree to totally disagree. The survey was online distributed using a large national panel in the Netherlands.

2.3.3.2 SAMPLE

Only people older than 18 were allowed to fill in this survey. In total 1,053 completed the survey. To avoid unreliable data, all respondents were filtered by two criteria, which are the time required to complete the survey and the answers given by rating the attitudinal statements. If a respondent rated each statement exactly the same, it is assumed that the respondent did not fill in the survey seriously. At the end a sample size of 761 respondents has been used, resulting in 4,566 observations.

A comparison was made between the sample and the Dutch population. It was concluded that the sample represents the Dutch population well.

2.3.3.3 MODEL

Two types of models were estimated: a latent variable model and discrete choice multinomial logit (MNL) model. The exploratory factor analysis is indicated by a latent variable model, and is showed in the equation below.

Equation 6

$$y_m = \Upsilon \eta_m + \varepsilon_m$$

Where Υ is a matrix containing factor loads of all manifest indicator variables y_m which are related to a specific latent construct η_m, for all latent constructs M, and ε_m being the measurement error. The factor scores of the resulting latent constructs are incorporated in as composite factors in the discrete choice model. The discrete choice model consists of three different components and is showed in the equation below.

Equation 7

$$U_m = \beta_x' x_m + \beta_\kappa' \kappa_m + \beta_\eta' \eta_m + \vartheta_m + \varepsilon$$

Where the first component consists of all the instrumental attributes and beta represents the importance of these attributes. The second part of the estimated models represents the socio-economic variables and its relative importance. η_m is the latent construct from the model described above. The component ϑ_m represents four nests, since unobserved communalities could occur between alternatives due to the egress modes. At last, the ε represents the error term. This methodology is applied in this study as well (see chapter 3).

2.3.3.4 RESULTS

It was found that the VOTT of full-automated vehicles users was higher than its manually driven counterpart and the private car users. This was an unexpected outcome. A second important outcome was that first-class travellers have a higher preference for AVs as last-mile transport compared to BTM and the bike. The VOTT values are shown in Table 2.10.

Table 2.10: VOTT outcomes (Yap et al., 2016).

Part of trip	*Mode*	*VOTT (€/h/person)*
Main	Private car	9.30 – 9.90
Egress	AV: manually driven	4.50 – 5.10
Egress	AV: full-automated	12.00 – 12.60

Yap et al. (2016) give different reasons why the VOTT of full-automated vehicles as egress mode is higher than the conventional car. Firstly, they give as possible explanation that respondents do not experience the benefits from automated driving yet. Secondly, respondents could feel uncomfortable and less safe in a full-automated vehicle. These two explanations have in common that no experience is endured with AV driving. A third argument is that an AV is used as egress mode, which covers mostly a short distance. During a short trip it has no use to open your laptop and start working, since the user is in a few minutes at his destination, and unpacking and packing time should be taken into account (Warffemius, Bruyn, & Hagen, 2016). A last explanation could be that AVs as egress mode are mostly attractive for first-class train travellers, which occur to have a higher VOTT by themselves.

The estimated parameters of the discrete choice model and the latent factors found in this study are relevant as well. Five latent factors have been estimated significantly that influences the appreciation of AV driving. These factors are trust in AV, service reliability, sustainability, productivity in an AV, and the perceived pleasure of driving a conventional car yourself. The relevant parameter estimations are shown in the next table.

Table 2.11: Relevant estimation results of discrete choice model (Yap et al., 2016).

Parameter	*Value*
In-vehicle_time_car	-0.031
In_vehicle_time_AV_automatically	-0.084
Walking_time	-0.073
Travel_costs_car	-0.20
Travel_costs_AV_automatic_second_class	-0.41
Trust_AV	1.53
Service-reliability_AV	0.65
Sustainability_AV	1.69
Productivity_in_AV_automatically	0.39
Enjoy_car_driving	-0.33

2.4 CASE STUDIES AV

The last paragraph of this chapter is dedicated to case studies that tried to deal with automated driving. Yap et al. (2016) did research about the VOTT of AV travellers, where AVs were used as last-mile transport. This study is already discussed below, and will not be discussed again in this paragraph.

2.4.1 SHARED AV AS MAIN MODE

Krueger et al. (2016) compared two shared AVs with an opt-out alternative. The distinction in AVs was as follows: one shared AV is with dynamic ride sharing (DRS) and the other without DRS. Data was gathered using SP choice experiments and with the data a mixed logit model was estimated. The main result is that the VOTT is lower for AV users without DRS than for AV users with DRS. Furthermore, service attributes like travel costs, travel time and waiting time are important facets for implementing and accepting shared AVs (with DRS) as travel mode.

2.4.2 FROM CONVENTIONAL CAR TO AV

Bansal et al. (2016) did research to the willingness to pay to upgrade a conventional car with AV specifications. Bansal et al. (2016) discovered that an important incentive to upgrade a manually driven car to a higher level automated vehicle is safety. The average found WTP for adding level 4 to a car is $7,253 and for level 3 $3,300. This study compared shared AVs with services such as UberX and Lyft as well. Bansal et al. (2016) found that respondents were overall not willing to pay more per mile for using a shared AV than these existing services ($1.50 per mile).

This chapter deepened into the literature regarding automated driving and the VOTT. It became clear that full-automated vehicles are vehicles where the sustained lateral and longitudinal vehicle motion control, object and event detection and response, and the dynamic driving task fall back are all coordinated by the automated driving system. The most important distinction between a high-automated vehicle and a full-automated vehicle is that the operational design domain is unlimited. This means that a full-AV is able to drive everywhere and a high-AV not.

Moreover, this chapter made clear that travel time could be beneficial if one is able to perform activities such as working or having leisure. We learned that the VOTT means the willingness to pay for a unit-travel time saving (WTP), which is derivable with a variety of methods, from which the discrete choice modelling is the most common method in transportation studies. At last, this chapter described several VOTT studies in the Netherlands, which will be used as reference work during the discussion of the results.

3 METHODOLOGY

In this chapter, a methodology is proposed to conduct the analysis. First it is explained why a stated preference experiment will be conducted. Then it deepens into different discrete choice models. Thirdly, the use of an additional factor analysis will be explained. The chapter ends with the model specification.

3.1 STATED PREFERENCE EXPERIMENT

Because there is no tangible market for selling and buying travel time, indirect methods must be used (Transportation BCA, 2016). The willingness-to-pay is usually calculated from discrete choice models, as the increase or decrease in utility of one unit divided by the change in utility by the price coefficient (Breidert et al., 2006). Whereas the VOTT is computed as the ratio between the travel time coefficient and the travel cost coefficient (Mackie et al., 2001). This method is applied in many studies over various years, for example Devarasetty et al. (2012); Tseng & Verhoef (2008); Yap et al. (2016), and will be used during this study as well.

Breidert et al. (2006) mentioned that two collection paradigms exist to derive the VOTT: revealed preference (RP) and stated preference (SP) (see Figure 2.1). In RP experiments people have to choose among existing, market-based measurements of attributes of alternatives, while stated preference provides a choice between a set of constructed measures of combinatorial mixes of attributes of real and/or hypothetical alternatives (Hensher, 1994).

The biggest advantage of RP data is that one observes what people actually choose; you have to make a choice between alternatives that exist in the real market. However, it has some limitations as well. Limitations are that the explanatory variables must be expressed in 'objective' or 'engineering' units, attendance of strong correlation between explanatory variables (multicollinearity), only existing alternatives can be observed, and there is often insufficient variation (Kroes & Sheldon, 1988). Since this research is about level 5 AVs, which are currently non-real market alternatives, the use of RP data is not desirable. Besides, it is already discussed in paragraph 2.2.2 that market data, laboratory experiments, field experiments and auctions are not appropriate methods to derive the VOTT of AV users.

It is concluded that this research requires SP data to answer its research questions. SP experiments offer solutions for all above limitations, and SP is easier to control, more flexible and less expensive to apply (Kroes & Sheldon, 1988; Molin, 2015a). A disadvantage of SP experiments is that respondents intend to choose the socially desirable answer (Kroes & Sheldon, 1988). The question is if whether this research requires direct surveys or indirect surveys.

With direct surveys, respondents are directly asked how much one is willing to pay for some product/service/transport mode, while in indirect surveys a ranking or rating procedure is applied. In this way the VOTT can be derived from conjoint analysis or discrete choice analysis (see Figure 2.1). It is argued that it is cognitively easier for respondents to decide whether a specific price for a travel mode and its travel time is acceptable rather than assign a price to it directly, since people make many choices every day (Brown et al., 1996). For this reason, it is chosen to make use of an indirect survey.

The last choice that has to be made is whether a conjoint analysis or a discrete choice analysis will be applied. To conduct a conjoint analysis, respondents have to rate each alternative (profile) on a rating scale, e.g. from 1 (very unattractive) to 10 (very attractive). When applying a conjoint analysis a regression analysis is conducted to estimate the model, where estimated parameters are weights; the contribution of each attribute level to the rating (attractiveness). This method is very simple to construct and is well applicable when there is only an interest in attractiveness or valuation. However, the relationship between the rating and the choice is not clear, and it has validation issues. Besides, since the 1990s it is hardly used in transport studies anymore (Molin, 2015a). To perform a discrete choice analysis, respondents are asked to make choices between alternatives, where utility is statistically derived from the discrete choice model. Choosing between alternatives is experienced to be easier for respondents than rating, thus it is more valid for behaviour analysis (Molin, 2015a). We can conclude that discrete choice modelling will be used to derive the VOTT of AV users.

3.2 RANDOM UTILITY MAXIMISATION VS. RANDOM REGRET MINIMISATION

The next step is to decide whether random utility maximisation (RUM) models or random regret minimisation (RRM) models are used. In the remaining part of this section it is explained what RUM and RRM contain and it is further substantiated which discrete choice method to use for this study.

RUM is based on the assumption that respondents derive utility from choosing alternatives. Utilities are latent variables, which are assumed by explanatory variables such as travel time, travel cost, comfort and so on. The observed preference indicators are manifestations of the underlying utilities. In this model it is assumed that respondents endeavour utility maximisation, and that one chooses the alternative, which generates most utility (Walker & Ben-Akiva, 2002). The biggest advantage of the RUM theory is that it is a convenient model form with known properties. Besides the inventor, McFadden, has won the Nobel prize in 2000. However, limitations are also found. The standard MNL model disregards heteroskedasticity in the error term, but this is tackled by using Nested Logit and Mixed Logit model. Secondly, the assumptions about the behaviour are debatable, since full compensatory behaviour exists across attributes (Dekker, 2013a).

Whereas RUM is a commonly used method, RRM can be seen as an alternative behavioural framework. In this method the chosen alternatives depend on the anticipated performance of non-chosen alternatives. In other words, this method assumes that a respondent's choice amongst a fixed set of alternatives is influenced by the desire to avoid the situation that one or more alternatives perform better than the chosen alternative on one or more attributes. Theory mentions that this causes regret, and the aim is to reduce regret as much as possible (Hensher, Greene, & Chorus, 2013). Zeelenberg & Pieters (2007) mention that minimising anticipated regret is an important factor in making important and difficult choices, provided that it influences significantly others in their social network. Hensher et al. (2013) argue that vehicle-type choices fit these conditions.

Altogether, it can be argued that both methods could be used during this research. Hess & Daly (2014) mention that in one-third of the cases the RUM model fits best, one-third of the cases fits the RRM model best, and in one-third of the cases a hybrid model fits best. The developments in RRM choice modelling show that besides the classical RRM model (Chorus, 2010) two new family members of the RRM family have been developed; μRRM and P-RRM (van Cranenburgh, Guevara, & Chorus, 2015). In this case a parameter, μ, is estimated which determines if a RUM model, classic RRM model or a P-RRM model fits the data best. In the case of a large μ the μRRM exhibits RUM behaviour. If the μ-parameter is estimated almost zero, a P-RRM model is estimated.

And at last if the μ-parameter equals (or is insignificantly different from) one the classic RRM model is applied (van Cranenburgh et al., 2015). Figure 3.1 shows that the larger the μ the more the μRRM exhibits RUM behaviour, since the line become more linear.

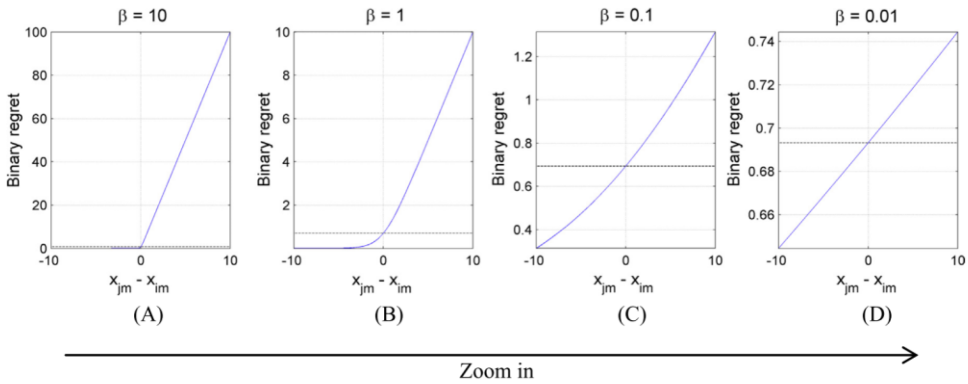

Figure 3.1: A-D: Shapes of the attribute level regret function for different sizes of the taste parameter, where $\beta = \beta_m/\mu$ (van Cranenburgh et al., 2015).

So for estimating behaviour, the μRRM is a good method to determine the type of RRM or RUM model. However, this study has the focus on VOTT exploration and does not have the focus on travel behaviour. Since the VOTT derivation from RRM models is more complex and less complete than using RUM models (Dekker, 2014), it is chosen to make use of the RUM methodology. Secondly, RRM's disadvantages are that the regret function is complex and runtimes of the model are significantly higher. Furthermore, the RRM is a new methodology, while policy makers and planners are familiar with RUM (Dekker, 2013b). Since the main focus of this research is on the possible VOTT (willingness-to-pay) changes and given the disadvantages of RRM, it is chosen to use the RUM method, because the VOTT computation is more practical and theoretically justified. Summarising, RUM is a familiar method to policy makers and planners, the VOTT computation is less complicated, and it is a convenient model form with known properties.

Next to these arguments, RUM models are extendable with extensions like: flexible disturbances, latent variable and latent classes, and it is suitable for combined RP and SP data (Walker & Ben-Akiva, 2002). Further, RUM decision-making models have their foundation in welfare economics (Bernheim & Antonio, 2011). CBA, that uses VOTT as important parameter, assesses projects embodied in a social welfare function (Drèze & Stern, 1987). So, it makes no sense to use a regret model since VOTT is context dependent and cannot be transferred to AV behaviour. A last argument for using RUM models is that RUM is already implemented in known software. Examples are Landelijk Model Systeem (LMS) (Haaijer et al., 2012) and Omnitrans (DAT.Mobility, 2014).

Multiple RUM models exists. In this study, multiple types of MNL models will be estimated, which are briefly discussed below.

3.2.1 MULTINOMIAL LOGIT MODEL

The most applied utility maximization model is the multinomial logit model. It is assumed in the MNL model that a respondent chooses the alternative that provides most utility. The probability that one chooses alternative A is:

Equation 8

$$P_A = \Pr\{U_A \geq U_B\}$$

Where P_A is the probability of choosing alternative A, U_A is the total utility of alternative A and U_B is the total utility of alternative B. The total utility (U_i) exists out of two components. The first component is the observed utility (V_i) like travel time and travel costs, while the second component indicates the unobserved utility (ε_i) like weather conditions (McFadden, 1981; Train, 2003).

Equation 9

$$\mathrm{U_i = V_i + \varepsilon_i}$$

It is assumed that the observed utility is linear-additive, so that the observed utility of an alternative can be written down as:

Equation 10

$$\mathrm{V_i} = \sum_{\mathrm{m}} \mathrm{\beta_m x_{mi}}$$

Where β_m indicates the utility parameter regarding attribute m, and x_{mi} represents the attribute value of attribute m for alternative i. In the case of labelled alternatives, an alternative specific constant (ASC) can be estimated. ASC represent the utility (preference) of the alternative itself in comparison to the other alternatives separated from observed utility. The logit model distinguishes itself by assuming that the unobserved utility component has an extreme value distribution. Another assumption where the MNL model relies on is the independence of irrelevant alternatives (IIA), what implies that the ratio of the probabilities of choosing any two alternatives is independent of the attributes or the availability of a third alternative (Hausman & McFadden, 1984). According this assumptions, the observed utilities can be transformed into probabilities by applied the logit formula (McFadden, 1974; Train, 2003).

Equation 11

$$\mathrm{P_i} = \frac{\mathrm{e^{V_i}}}{\sum_{\mathrm{j}} \mathrm{e^{V_j}}}$$

The goal of estimating a MNL model is to find the model parameters (βs) that provide information about the preferences of the decision makers. The most common method to estimate the choice model is maximum likelihoods estimation (MLE). MLE aims to find the parameters that fits the observed data the best. The likelihood is the product of the choice probabilities of the chosen alternatives. However for numerical reasons the log-likelihood has been applied as shown in the next formula.

Equation 12

$$\mathrm{LL(\beta)} = \sum_{n} \sum_{i} y_{in} \ln P_n(i|\beta)$$

Where y_{ni} is 1 if indicator n has chosen alternative i, otherwise 0. The closer the value of the log-likelihood to zero, the better the model represents the choices made by the decision makers (McFadden, 1974; Train, 2003). With the log-likelihood the fit of the model can be examined, making use of McFadden's rho-square.

Equation 13

$$\rho^2 = 1 - \frac{\mathrm{LL}(\hat{\beta})}{\mathrm{LL}(0)}$$

In this equation the *LL(0)* indicates the log-likelihood of the data in the case the choices are made with equal probability. The interpretation of the rho-square, which is always between 0 and 1, is shown in the next table.

Table 3.1: Interpretation of McFadden's Rho-Square.

Rho-square value	*Interpretation*
$\rho^2 < 0.1$	The model explains the data in a very limited way
$0.1 < \rho^2 < 0.3$	The model explains the data reasonably
$0.3 < \rho^2 < 0.5$	The model explains the data well
$\rho^2 > 0.5$	The model explains the data very well

McFadden's rho-square is an universal method to test the fitness of a discrete model. It is not only applicable to the MNL model, but to the NL model, ML model, and the LC model as well. Furthermore, the MNL model is the most used discrete choice model, because it is relatively easy to estimate and to understand. The latter models that are explained below are all based on the MNL model, since the MNL model has its limitations. Firstly, the MNL model does not easily accommodate the presence of preference heterogeneity within choice data. A second limitation is that it does not accommodate panel effects, meaning that it cannot cope with multiple choice observations per decision maker. At last, the MNL model imposes a constant error variance assumption across all alternatives within the model (Bliemer & Rose, 2010).

3.2.2 NESTED LOGIT MODEL

Nested logit is an approach that generalises the MNL model by allowing correlation between the non-observed utilities of groups of alternatives. However, the remaining restrictions on the equality of cross-elasticities between pairs of alternatives in or not in common nests may be unrealistic in important cases. The NL model is derived from McFadden's (1978) generalised extreme value model (Wen & Koppelman, 2001). A well-known example of correlation between alternatives is the case of a car, and a red and a blue bus. A MNL model overestimates the choice probabilities of the bus alternatives, because the MNL model assumes that all unobserved utilities are independently distributed.

By constructing a NL model one must recognise (or test) the possibility that the standard deviations of the random error component in the utility expressions are different across nests of alternatives in the choice set (Hensher & Greene, 2002). Within the nest applies the IIA assumption, however between the nests this assumption expires. Having this said, the logit formula used in the MNL is in the NL adapted as follows.

Equation 14

$$P_i = \frac{e^{\frac{V_i}{\lambda_k}} \left(\sum_{j \in B_k} e^{\frac{V_j}{\lambda_k}} \right)^{\lambda_k - 1}}{\sum_{l=1}^{L} \left(\sum_{j \in B_l} e^{\frac{V_j}{\lambda_l}} \right)^{\lambda_l}}$$

In this formula P_i represents the probability of alternative *i*, which is in nest *k*. The V_i is the observed utility of alternative *i*. B_k is the set of alternatives that belong to nest *k*, and *L* represents all nests. Parameter λ_k is the nest parameter that indicates the degree of correlation between the error components of the alternatives within nest *k* (Train, 2003). The nest parameter is always between 0 and 1, meaning that the closer the parameter is to 0 the more correlation between the unobserved utility components of the alternatives in the nest. In the case of no correlation, λ becomes 1 and the logit formula of the MNL occurs.

3.2.3 MIXED LOGIT MODEL

Mixed logit solves three main problems of the standard MNL model, namely it allows random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train, 2003). The distribution of the VOTT could be of importance for example when forecasting market shares for a tolled road (Hensher & Goodwin, 2004). The mixed logit allows that the parameter vector β used in the computation of the utility are randomly distributed rather than fixed (Hess et al., 2005). In the current MNL model the parameter vector is the same for all respondents, however the ML model distributes the parameter vector randomly over the respondents. Nonetheless, the β do not vary within the choice tasks of the same respondent. In the ML model the choice probability for alternative i and decision maker n, $P_{ni}(\beta, x_{ni})$, is replaced by:

Equation 15

$$P_{ni} = \int_{\beta} P_{ni}(\beta, x_{ni}) f(\beta, \Omega) d\beta$$

Where Ω is a vector of parameters of the distribution of the elements contained in the vector β (Hess et al., 2005). The distribution of the parameters is either bounded or unbounded. In transportation research the travel-time coefficient is commonly distributed making use of the normal (Gaussian) distribution or the log-normal distribution. The side-effect of using this unbounded distribution is that in theory the travel-time coefficient could become positive, which results in a negative VOTT (Hess et al., 2005). For this reason Hess et al. (2005) recommend using bounded distributions such as the triangular or Johnson's S_B distribution (Train & Sonnier, 2005) where the bounds are estimated from the data itself. The chosen distribution can have a considerable impact on the results of the study (Hensher, 2001b). Unfortunately, little evidence exists to guide the choice of distribution.

The ML model allows also panel effects. The MNL models assumes that choices made by the same individual are uncorrelated, while correlation is generally observed. This property of the MNL model results in underestimating the standard errors, and therefore in overestimating the t-values of parameters such that insignificant parameters are estimated significantly (Chorus, 2016).

3.3 EXPLORATORY FACTOR ANALYSIS

In the SP choice experiments the role of classical instrumental variables as travel time and travel costs are explored. Besides that, it will cope with socio-economic factors as 'car ownership', 'gender' and 'income class'. However, in this case a driver has to trust completely on a computer. Thus, sensitivity could play a role, which is also mentioned in Yap et al. (2016). Since attitudes against the use of AVs are often implicit and cannot be measured directly (Yap et al., 2016), an exploratory factor analysis will be performed to investigate the underlying latent factors. A latent variable model is estimated to measure the underlying attitudinal factors.

An exploratory factor analysis (EFA) is a technique to explore the possible underlying structure of a set of interrelated variables without imposing any preconceived structure of the outcome (J. S. Williams & Child, 2003). It is a method that reduces variables which identifies the number of latent constructs and the underlying factor structure of set variables. Measurement tools like attitudes towards automated driving and satisfaction scales can be used to conduct an EFA (Suhr, 2006).

The technique aims to put as much as possible common variance in the first extracted factor. The second till last factor intends to account for the maximum amount of remaining common variance until (almost) no common variances exists (Suhr, 2006).

The Eigenvalue (Kaiser) criterion determines the initial estimated amount of factors (Kaiser, 1960). If the Eigenvalue of a factor is higher than one, it is considered as a common factor (Nunnally, 1978). Next to the Eigenvalue criterion, the scree plot criterion will be applied. The scree plot shows the Eigenvalues of all initial components. From the component the line flattens out, this particular component as well as all the remaining components are excluded from further analysis. This could result that a factor with an Eigenvalue of for example 0.95 will be used as factor in the model.

To come up with relevant factors, rotations techniques are used. Roughly two rotation techniques are used: orthogonal rotation and oblique rotation (Abdi, 2003; Suhr, 2006). In the orthogonal rotation the axes are kept at an angle of 90 degrees, where in the oblique rotation this constraint is gone. The most popular rotation method is the VARIMAX rotation, which is an orthogonal rotation. This method aims to highly load each variable to one (or a small amount of) factor(s), and each factor represents only a small number of variables (Abdi, 2003). Two other orthogonal rotation techniques exists: QUARTIMAX and EQUIMAX, where QUARTIMAX minimise the number of factors for explaining each variable. EQUIMAX is a combination of VARIMAX and QUARTIMAX (Abdi, 2003).

The oblique rotation is not delimited to axis angles of 90 degrees. The degree of correlation allowed between factors is mostly small, because two highly correlated factors explain more than one factor. So, this method is established to simplify the interpretation of the obtained factors. However, this method is scarcely used in comparison with the VARIMAX method (Abdi, 2003). Thus the EFA for this study will make use of the VARIMAX rotation.

Different manifest indicators, in the form of statements, are used as input to measure attitudes towards automated driving. Respondents have to assign a grade on a Likert-scale on how much they (dis)agree with a certain statement. To have a neutral option as well, an odd number of options will be used (Wakita, Ueshima, & Noguchi, 2012). However, to avoid that respondents choose the neutral (uncertain) alternative too often it is recommended to use a scale higher than the 3- or 5-point rating (Matell & Jacoby, 1972). Therefore, for this research it is chosen to use a 7-point Likert scale, where 1 is related to *totally disagree* and 7 is related to *totally agree*.

3.4 MODEL SPECIFICATION

The last paragraph provides the applied model specification. It contains the model specification for the MNL model, NL model and ML models. It is assumed that each individual chooses alternative *i* if the utility $U_i > U_{j \neq i}$. Then, for each of the 12 alternatives *i* included in the choice sets, the utility of the MNL model can be calculated with Equation 16.

Equation 16

$$U_i = \alpha_i + \beta_x' x_i + \beta_\tau' \tau_i + \beta_\eta' \eta_i + \varepsilon_i$$

Where x_i consists of all instrumental SP attributes, and β'_x represents a vector that represents the parameter value of all SP variables x included in the alternative specific utility function U_i. α_i is the unobserved preference for alternative *i*. It is assumed that the first part of the utility function is linear. The aim is to estimated mode-specific parameters regarding the SP variables.

The second part of the utility function represents the addition of socio-demographic variables (τ_i) of each alternative *i*. These variables are added to increase the explanatory power of the model. β_τ is a vector that represents the importance of the different socio-demographic variables τ.

The third part represents the latent variable model. To do a latent variable model manifest indicators, showed statements, must be rated by respondents. In total 18 attitudinal statements have to be rated by respondents. The statements are presented in paragraph 4.3. The ratings of the indicators are used as input for the latent variable model. Equation 17 shows for the 18 attitudinal statements the measurement equations as specified in the EFA. This indicates the latent variable model. Ψ represents a matrix with factor loadings of all attitudinal indicators y_i. The attitudinal indicators are related to a latent construct η_i for all latent constructs *I*. ε_i represents the measurement error (Temme, Paulssen, & Dannewald, 2008).

Equation 17

$$y_i = \Psi\eta_i + \varepsilon_i$$

A hybrid choice modelling approach is applied, where the latent variable model and the discrete choice models are estimated sequentially. This means that first the latent variable model is estimated, which results in factor scores for each latent attitudinal construct. The computed factor scores substitute the latent variables in the discrete choice models as error-free exogenous variables (Temme et al., 2008). This method is, however, deficient such that it is not capable of investigating behavioural relationships between socio-demographic, latent attitudinal constructs and SP attributes (Walker & Ben-Akiva, 2002). Estimating the latent variable model and the discrete choice models simultaneously overcomes this limitation. However, the computation time increases exponentially by the number of factors (Temme et al., 2008). So, for the exploring nature of this research, it is determined that a sequential estimation fulfils the requirements to measure if attitudes towards automated driving influence the choice-behaviour.

The β'_τ vector in Equation 16 represents the importance of the factors η_i. At last, the ε_i represents the independent and identically distributed (i.i.d.) error component of utility function U_i.

For the NL model, Equation 16 has been slightly adapted. In the MNL model the IIA assumption holds, however in the NL model the IIA assumption only holds within a nest but not between nests. This means that correlation among alternatives is accepted.

The ML models have an additional disturbance related to Equation 16, such that the utility function of alternative *i* is:

Equation 18

$$U_i = \alpha_i + \beta'_x x_i + \beta'_\xi \xi_i + \beta'_\tau \tau_i + \beta'_\eta \eta_i + \varepsilon_i$$

Where ξ_i captures the unobserved part of the utility. $\xi_i \sim D(\Theta_\xi)$, Θ_ξ being a set of parameters, is a flexible disturbance, which allows one to impose distributional assumptions on random parameters (Krueger et al., 2016). In this study the normal distribution is used for the mode-specific time parameters and the unobserved preference (alternative specific constant). The other parts of the utility function are the same as in Equation 16.

For synthesis, this chapter contained four parts. In the first part it is explained why SP experiments are most suitable for this study. In the second part it was concluded that random utility maximisation based discrete choice modelling is the most suitable method for this study. This part proposed three different types of RUM models that will be applied. Then, in part three it is concluded that a latent variable model will be estimated as well to measure underlying attitudinal factors that could influence the decision-making. In the last part it is concluded that a hybrid choice modelling approach will be applied where the latent variable model and the discrete choice models will be estimated sequentially.

4 SURVEY REQUIREMENTS

Chapter 4 provides insights in the elements that the final experiment should include. Firstly, information about the stated-preference experiment requirements is given. Then, it is explained what steps are required to conduct the exploratory factor analysis. Ultimately, subsection 4.2 is devoted to designing the stated preference experiment.

4.1 STATED PREFERENCE EXPERIMENT REQUIREMENTS

At least two alternatives must be defined to conduct a SP experiment. Alternatives vary along attributes, which have at least two attribute levels. Besides the choice sets, it is common to obtain information of every respondent through questions about his or her socio-demographic situation. Since one of the objectives is to measure if a difference exists in trip experience when one is driven by a computer or by a human (see paragraph 1.4.4), two identical surveys will be held. One survey, which measures the experience of AVs compared to conventional cars and a second experiences which measures the experience of chauffeur-driven cars compared to conventional cars.

4.1.1 ALTERNATIVES, ATTRIBUTES & ATTRIBUTE LEVELS

This subsection provides an explanation of the choices regarding the alternatives, attributes, and attribute levels.

4.1.1.1 ALTERNATIVES AND ENVIRONMENTAL CONTEXT

Each choice set has three alternatives. One alternative is the conventional car and two alternatives are AV/chauffeur-driven car (CH) alternatives. The two AV/CH alternatives are an AV/CH with office interior and an AV/CH with leisure interior. It is important to inform the respondents about the different interiors. Therefore elaborated descriptions of the AV/CHs are given. Visualisations of how an AV-office or AV-leisure could look like is shown to the respondents as well.

Besides the alternatives, a context in which choices have to be made is required. The context at which the choices take place is the morning peak, meaning trips from home to work. At every choice task the assumption in the form of 'Assume your next trip is a trip from home to work …' was proposed.

4.1.1.2 ATTRIBUTES & ATTRIBUTE LEVELS

The next step is to identify attributes and attribute levels to differentiate alternatives from each other. When looking at other studies, e.g. (Arentze & Molin, 2013; Krueger et al., 2016; Rose, Bliemer, Hensher, & Collins, 2008; Yap et al., 2016), travel time, travel costs, walking time, waiting time, fuel costs and parking costs are commonly used attributes. Since (in-vehicle) travel time and travel costs are required to determine the VOTT, it is necessary to include these attributes at least.

Travel time The average time per commuting trip for car users is 29.65 minutes in 2015 in the Netherlands (CBS Statline, 2016h). It is chosen to use three attribute levels for travel time (15 min, 30 min, 45 min). It is expected that an increase in travel time has a negative effect with regards to AVs.

Travel costs Barnes & Langworthy (2004) state that driving costs exist out of 4 components: fuel, maintenance/repair, tires and depreciation, whereas fuel costs are responsible for 37% of the total costs. The average Dutch commuting trip takes approximately 30 minutes and the average distance driven during this time frame is about 19 km (CBS Statline, 2016h). The average fuel consumption for European petrol and diesel cars is 0.081 L/km and 0.61 L/km respectively (Ntziachristos et al., 2014). The average fuel price in the Netherlands over the period February 2015 and September 2016 is €1.52 per litre for petrol and €1.18 per litre for diesel (CBS Statline, 2016i). This gives €2.33 and €1.37 for petrol and diesel cars respectively as fuel costs. The ratio of petrol and diesel cars (CBS Statline, 2016f) provides a weighted fuel price of €2.17 for 19 km travelling by car. Assuming that €2.17 is 37% of the total travel costs, the total costs for travelling 19 km is approximately €6. Making use of this cost approximation, the attribute levels for travel costs are fixed on €4.50, €6.00, and €7.50. Parking costs are not included in this study.

Walking time The third attribute is the walking time to the destination. It is assumed that AVs bring persons to the doorstep, which is why this attribute is always indicated as 0 minutes for AVs. Walking time is expressed as the time one needs to walk from the parking space to the final destination. It is chosen to limit these attribute levels to 2 min, 4 min and 6 min. Waiting time is not included in this study, since it holds only for shared transport (e.g. car-pooling) or public transport.

Travel company Because it is imaginable that choices are made differently if one travels alone or accompanied an attribute regarding travel companions is included. The vehicle occupation consists of two levels: travel alone, and travel with family and/or friends.

Activity König & Neumayr (2017) found that the possibility to engage in other activities while driving is one of the main benefits of AVs. Six categories of activities that are executable in a car are defined in the literature: leisure, eating, rest, communication, cleanliness and working. The leisure activity consists of many activities such as reading, gaming and shopping. The category cleanliness implies changing clothes, refresh yourself and putting on make-up. The most chosen activities to do in an AV by drivers are leisure, working and resting (Kim, Yoon, Kim, & Ji, 2015). It is chosen to define only two AV activity categories: have leisure time or work.

It is assumed that if one chooses the AV/CH-leisure, one does automatically have leisure time. For the AV/CH-office this is determined differently. A distinction has been made in the category work: you either work extra time or you reduce time at the office. Figure 4.1 provides an overview of the different activities. This concludes that three different activities are defined: working extra time, saving working time at the office and having leisure time, where activities only vary within the office-AV alternative.

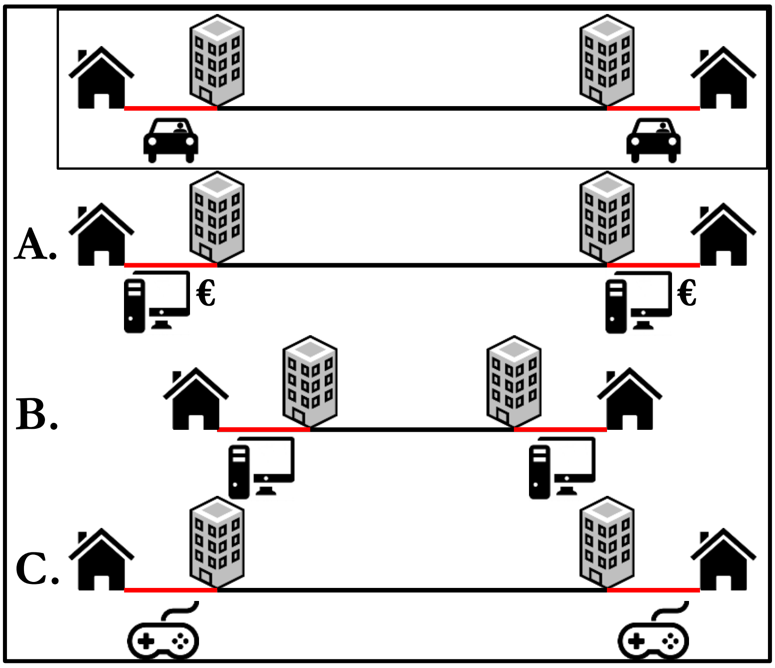

Figure 4.1: Identified AV activities. From top to bottom: current situation, A. work extra time, B. save working time at office, C. have leisure time.

For synthesis, Table 4.1 provides an overview of the attributes and the attribute levels used in the SP experiment.

Table 4.1: Overview of final attributes and attribute levels used in the SP experiment.

Attribute	*Attribute level*			
Walking time to destination	0 min	2 min	4 min	6 min
In-vehicle travel time	15 min	30 min	45 min	
Travel costs	€4.50	€6.00	€7.50	
Travel companions	Alone	Family and/or friends		
Activity	Work extra time (AV-office)	Save time at the office (AV-office)	Have leisure time (AV-leisure)	Drive the car (car)

4.1.2 SOCIO-DEMOGRAPHIC DATA

Socio-economic variables are observable variables, which provide information about the respondent. Examples are gender, employment status and car ownership. Socio-economic data will be used as validation whether the samples are representative for the Dutch population, and as additional explaining variables. Table 4.2 shows an overview of the socio-economic variables that will be measured.

Table 4.2: Socio-economic variables and their categories for in the estimated model.

Socio-demographic variable	*Categories in estimated model*	*Question*	*Answer(s)*
Age	<20 20-39 40-64 65-79 >80	How old are you?	… years old
Car ownership	Yes No	Do you own a car?	Yes, no
Driving license	Yes No	Do you possess a driving license?	Yes, no
Educational level	Low Medium High	What is your highest level of education?	Primary, MAVO/VMBO, HAVO, VWO, MBO, HBO, WO
Gender	Male Female	What is your gender?	Male, female
Net income class (€/year)	< €10.000 €10.000 - €19.999 €20.000 - €29.999 €30.000 - €39.999 €40.000 - €49.999 > €50.000	What is your current yearly net income?	€ … per year
Daily business	Work full time Work part time Study Retired None of above	What is your daily participation?	Work full time, work part time, study, retired, n.o.a.
Able to work in an AV	Yes No	Is your work possible to be done in a comfortable car with internet and no trepidation?	Yes, no
Willing to work in an AV	Yes No	Are you willing to work in an AV?	Yes, no
Current door-to-door travel time (min/one-way trip)	<30 minutes 30-60 minutes >60 minutes	What is your current door-to-door travel time?	… minutes per one-way trip
Buying an AV	Yes No	Would you, given the information, consider buying an AV for the same price as a normal car?	Yes, no
Travel expenses reimbursement	Yes No	Do you get a reimbursement for travel expenses you make for your work?	Yes, no
Most commonly used mode	Car, bike, train, BMT, car-pooling	What is your most commonly used mode of transport?	Car, bike, train, BMT, car-pooling

It is chosen to divide the net income per year in six categories, since the Dutch census uses these categories (CBS, 2015b). Furthermore, the educational level of the Dutch population is divided in three categories: low, medium and high (CBS, 2013; CBS Statline, 2016b). Because the Dutch census bureau categorise the population in five age groups (CBS Statline, 2016c) it is chosen to adopt these age categorisation as well.

4.2 EXPERIMENTAL DESIGN DETERMINATION

Last step is to determine with what design the choice sets will be constructed. An experimental design visualises which hypothetical choice sets the respondents are faced with in the SP experiment. ChoiceMetrics (2014) provides a set of questions that has to be answered before constructing the final experimental design. These questions are:

- Should the design be labelled or unlabelled?
- Should the design be attribute level balanced?
- How many attribute levels should be used?
- What are the attribute level ranges?
- What type of design should be used?
- How many choice situations should be use?

Labelled alternatives are required in the case that alternative specific parameters are estimated in the model specification. Alternative specific parameters for the conventional car (walking time) and the AV/CH with office interior (AV/CH activity) are used. This means that the design requires labelled alternatives.

Attribute level balance means that the same number of observations for each attribute level is obtained during the survey. The result of attribute level balance is that all the parameters estimated for the attributes have the same standard error, thus having the same reliability (Molin, 2015b). Besides, attribute level balance is considered as a desirable property in a design (ChoiceMetrics, 2014). It is therefore chosen to apply attribute level balance in this survey.

Generally spoken, an increase in attribute levels demands an increase in choice sets. In this survey, three attribute levels are used in the travel costs, travel time, and walking time variables. For the AV activity attribute an effect coding will be used, since effect coding assures that every attribute value has a part-worth utility.

A wide attribute level range is statistically preferable since it leads to better estimated parameters. However, too large attribute ranges could lead to choice tasks with too much dominance. Having too small ranges makes it difficult for the respondents to distinguish the alternatives (Rose & Bliemer, 2013). It is decided to use a range of 30 minutes for travel time [15, 30, 45], of 4 minutes for walking time [2, 4, 6] and of 3 euros for travel costs [4.5, 6, 7.5].

The next question is if a full factorial design or a fractional factorial design should be used. The full factorial design consists of all possible choice sets. The fractional factorial design uses a fraction of the full factorial design. Many types of fractional factorial designs exist, whereas two classes are mostly used: orthogonal design and efficient design. The orthogonal design aims to minimise the correlation between the attribute levels in the choice sets, while the efficient design aims to be statistically as efficient as possible in terms of predicted standard errors of the parameters (ChoiceMetrics, 2014).

Two classes exist within the orthogonal design. The sequential orthogonal design first constructs alternatives from experimental design, and then one has to decide how many alternatives are required per choice set. For every alternative a separate urn is constructed which draws randomly choice sets from the first urn. Imagine the first urn consists nine alternatives named alternative 1 to 9. Then, the first alternative in urn two is randomly drawn from urn one. So alternative 1 could be coupled to alternative 9 in the second urn, 2 to 8 and so on (Molin, 2015b).

One disadvantage of the sequential orthogonal design is that every alternative must have the same attributes and attribute levels (ChoiceMetrics, 2014). So, in this study the sequential orthogonal design is eliminated. The simultaneous orthogonal design does not have this delineation. This experimental design is used to simultaneously construct the alternatives, which results in uncorrelated alternatives (Molin, 2015b).

The third fractional factorial design is the efficient design. Three ways exist to measure the efficiency of the designs: D-efficiency, A-efficiency, and S-efficiency. The difference between these methods is that A-efficient designs are based on the trace of the asymptotic variance-covariance (AVC) matrix, the D-efficient design is based on the determinant of the AVC matrix, and S-efficient designs tries to minimise the standard error of the parameter which is hardest to get significant. The most common used efficient design is the D-efficient design (ChoiceMetrics, 2014). More information about orthogonal and efficient designs can be read in (ChoiceMetrics, 2014; Rose & Bliemer, 2009; Rose et al., 2008)

Since an orthogonal design is not always in line with many of the desirable properties of logit and probit models and efficient designs are (Rose & Bliemer, 2009), it is chosen to make use of a D-efficient design. For constructing efficient designs a prior estimate of the parameter is required. It is chosen to follow common practice: first a survey is distributed to determine usable priors, then the two final surveys will be designed and distributed. The prior-estimation experiment and the final experiments are explained in the next chapter.

4.3 EXPLORATORY FACTOR ANALYSIS REQUIREMENTS

Attitudes regarding automated driving could play an important role in the trading behaviour. Yap et al. (2016) found that attitudinal factors towards automated driving influence the choice behaviour regarding AVs. Manifest indicators are required to perform an exploratory factor analysis.

The list below shows all the manifest indicators that respondents have to rate. The statements are partly based and adopted from Carlson et al. (2011), Casley, Jardim & Quartulli (2013), Merritt, Heimbaugh, LaChapell & Lee (2012), Payre, Cestac & Delhomme (2014), and Yap et al. (2016).

1. I enjoy driving a car myself.
2. I would like to purchase an automated vehicle if it has better fuel efficiency than its conventional counterpart.
3. I trust that a computer can drive my car with no assistance from me.
4. I would be comfortable entrusting the safety of a close family member to an automated vehicle.
5. I think an individual requires a driving license before driving in an automated car.
6. I like it that I can be more productive on other tasks if I am riding in an AV.
7. I like it that I can delegate the driving to the automated driving system if I am due to certain circumstances not able to drive myself.
8. I like it that the automated car produces fewer pollutant emissions.
9. I like it that the car can park itself at cheaper parking spaces away from my destination.
10. I am afraid that the automated vehicle will malfunction.
11. I dislike the idea of automated driving.
12. I am afraid that the automated vehicle will not be fully aware of what is happening around him.
13. I do not like it that I do not have control of how the automated car drives.

14. I think that the automated driving system provides me more safety compared to manually driving.
15. I wish that automated vehicles were not around in the future.
16. I like it if I can recover control from the automated pilot if I do not like the way it is driving.
17. I like it that automated vehicles can adapt routes to avoid congestion.
18. I am afraid that I get motion sickness while riding in an automated vehicle.

This chapter discussed the survey requirements. It was decided that the SP experiments contain three alternatives: conventional car, the AV/CH-leisure and the AV/CH-office. Next, we conclude that using five attributes (travel costs, travel time, walking time, activity in AV/CH and travel company) fulfils the aim of the study. Furthermore it is proposed to use the trip purpose 'from home to work'. Then, it was concluded in the second part to let the respondents rate 18 attitudinal statements on a 7-point Likert scale. These ratings will be used as input for the EFA. At last, it is decided to use a D-efficient experimental design for constructing the choice tasks.

5 CONSTRUCTING THE FINAL EXPERIMENTS

This chapter contains the last step in constructing the finals experiments. The previous chapter ended with the conclusion that priors are required to construct a D-efficient design. The first subsection deepens into the construction and execution of the prior study. Subsequently, in subsection 5.2, the outline of the final experiments are given.

Note: The prior estimation study is conducted after completing the final survey. However, thanks to feedback from the respondents of the prior-study and some new insights the final survey has been adapted and improved. All alternatives, attributes, attribute levels, and the context provided in the previous chapter belong to the final survey version constructed <u>after</u> the prior-estimation study.

5.1 PRIOR ESTIMATION STUDY

For the *prior-estimation* survey an efficient design is used as well. The priors used for the *prior-estimation* survey are adapted from literature (Arentze & Molin, 2013; Haboucha et al., 2017; Krueger et al., 2016; Yap et al., 2016).

5.1.1 DESIGN PRIOR ESTIMATION STUDY

Four priors were estimated for travel time, travel costs, walking time and activity (*note: at the time of distributing this survey, the 'company' attribute was not yet defined*). The used priors for the prior survey are shown in Table 5.1.

Table 5.1: Used priors in the prior-estimation survey.

Parameter	*Prior value*
β_{TRAVEL_TIME}	-0.3
β_{TRAVEL_COSTS}	-2.0
$\beta_{WALKING\_TIME}$	-0.7
$\beta_{ACTIVITY}$	-0.5

A D-efficient design including 12 choice sets was constructed with the software package NGENE (ChoiceMetrics, 2014). Effect coding is used for the 'activity' attribute levels, where working extra time is set on +1 and save time at the office is set on -1. The D-error is 0.106. The *prior-estimation* survey is shown in Appendix A. The survey was in Dutch and included only 12 choice tasks in a commuting context; no socio-demographic information had been asked. Secondly, the survey is mostly distributed to friends, family and colleagues of the researcher and the first supervisor (dr. ir. G. Homem Almeida de Correia).

5.1.2 RESULTS PRIOR ESTIMATION STUDY

70 Respondents completed the survey resulting in 840 observations. Different multinomial logit (MNL) models were estimated with the software package BIOGEME (Bierlaire, 2003). The utility functions of the final prior-estimation model were defined as follows:

Equation 19

$$V_{CAR} = \alpha_{CAR} + \beta_{TT\_CAR} \cdot TT_{CAR} + \beta_{TC\_CAR} \cdot TC_{CAR} + \beta_{WT\_CAR} \cdot WT_{CAR}$$

Equation 20

$$V_{AVO} = \alpha_{AV} + \beta_{TT\_AVO} \cdot TT_{AVO} + \beta_{TC\_AVO} \cdot TC_{AVO} + \beta_{AC\_AVO} \cdot AC_{AVO}$$

Equation 21

$$V_{AVL} = \alpha_{AV} + \beta_{TT\_AVL} \cdot TT_{AVL} + \beta_{TC\_AVL} \cdot TC_{AVL}$$

The statistics of the final model used for prior-estimation are shown are Table 5.2. It shows that the model fits the data reasonably well (adj. Rho-Square > 0.10) and that this final model fits significantly the null model (all parameter values are equal to zero).

Table 5.2: Statistics prior-estimation discrete choice model estimation.

Number of observations	840
Number of estimated parameters	9
Null log-likelihood	-922.834
Final log-likelihood	-768.733
Likelihood Ratio Test (LRS)	308.202
Adjusted Rho-Square	0.157

In the MNL prior-estimation model nine parameters are estimated. The results of the prior-estimation discrete choice model are shown in Table 5.3. Where AVO stands for AV with office interior and AVL means AV with leisure interior.

Table 5.3: Estimation results of prior-estimation discrete choice model (travel time in minutes, travel costs in euros).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	-3.48	1.44	-2.42	0.02	1.19
Constant_AV	0.00	-	-	-	-
Traveltime_car	-0.0708	0.0149	-4.75	0.00	0.0212
Traveltime_AVO	-0.108	0.0174	-6.20	0.00	0.0202
Traveltime_AVL	-0.128	0.0150	-8.50	0.00	0.0203
Travelcosts_car	-0.274	0.0922	-2.97	0.00	0.106
Travelcosts_AVO	-0.543	0.0932	-5.83	0.00	0.116
Travelcosts_AVL	-0.582	0.122	-5.20	0.00	0.127
Walkingtime_car	-0.132	0.0389	-3.39	0.00	0.0481
Activity_AVO	-0.304	0.0880	-3.45	0.00	0.0975

The discrete choice model estimated the parameter sign according expectation. The model output indicates that an unobserved preference for the AV is exists (-3.48). Some of the estimated parameter values of the *prior-estimation* study have similarities with the estimated parameters of Arentze & Molin (2013).

With this outcome it is possible to get a first insight whether the expectation is correct. When calculating the VOTTs by the ratio of the travel time parameters and the travel costs parameters it appears that the VOTT for the users of both the AVs is lower than the conventional car users. The VOTT for the car user is €0.258 per minute per person, the VOTT for the AV-office user is €0.199 per minute per person, and the VOTT for the AV-leisure user is €0.220 per minute per person. It is important to assess whether the estimated ratios are significantly different from zero. The Delta method is a method to approximate the true values of the standard error (Daly, Hess, & de Jong, 2012). An explanation of the Delta method and the computation of the standard errors of the VOTTs can be found in Appendix C. It indicates that the standard error of the VOTT of car users is 0.09 thus significant in the 95% reliability level. The standard errors of the office-AV user and the leisure-AV user are respectively 0.02 and 0.03. This means that all ratios are significantly different from zero.

5.1.3 CONCLUSION PRIOR ESTIMATION STUDY

It is calculated that the VOTT of the office- and leisure-AV users are respectively €11.93 per hour per person and €13.20 per hour per person, while the VOTT for car users is €15.50 per hour per person. This model shows that the prior-results are in line with the expectation. However the prior-estimation survey had shortcomings such as no available socio-economic data, no attitudinal data, and no verification whether the sample is comparable to the population. Furthermore, it is notable that the VOTT for car travellers is higher than the €9.00 per hour found by Kouwenhoven et al. (2014), but approximately similar to the value found in Arentze & Molin (2013).

The priors regarding the efficient designs of the final survey are shown in Table 5.4. Note that the prior value for the travel company attribute is not based on this study. The same prior value for travel costs is used in the final experiments. The prior value for the travel time parameter for both AV alternatives is the same as well.

Table 5.4: Used priors in the final experiments.

Parameter	*Prior*
$\beta_{CONSTANT\_CAR}$	-3
$\beta_{TRAVEL\_TIME\_CAR}$	-0.07
$\beta_{TRAVEL\_TIME\_OFFICE\_AV}$	-0.1
$\beta_{TRAVEL\_TIME\_LEISURE\_AV}$	-0.1
$\beta_{TRAVEL\_COSTS\_CAR}$	-0.5
$\beta_{TRAVEL\_COSTS\_OFFICE\_AV}$	-0.5
$\beta_{TRAVEL\_COSTS\_LEISURE\_AV}$	-0.5
$\beta_{WALKING\_TIME}$	-0.1
$\beta_{ACTIVITY}$	-0.3
$\beta_{TRAVEL\_COMPANY}$	-0.1

5.2 OUTLINE FINAL EXPERIMENTS

Subsection 5.2 gives an overview of the final experiments. Respondents had the ability to give feedback on the prior-estimation survey. With the input from respondents and the results of the survey adaptations are made in the survey, which are discussed in subsection 5.2.1. The last paragraph of this chapter provides an example of the outline of the final survey.

5.2.1 ADAPTATIONS IN THE FINAL SURVEY THANKS TO PRIOR-ESTIMATION STUDY

Multiple respondents suggest that the context was confusing. In the prior survey it was proposed that a respondent had to imagine that his/her next trip is a commuting trip. However, it is a big difference whether one travels to work in the morning or one travels back home in the afternoon. It is imaginable that one prefers to start doing working activities the morning, while relaxing is more preferred on the way back home. Since it is more common to investigate mode choice and appreciation in during the morning peak, it is chosen to use the morning peak to this research as well.

- Adjustment 1: Commuting context → morning peak (travel from home to work) context

In the prior experiment the attribute levels of the in-vehicle travel time were fixed on 20 minutes, 30 minutes, and 40 minutes. The walking time attribute levels varied between 3, 6, and 9 minutes. Respondents noticed that due to the relatively small range of the in-vehicle travel time and the relatively large range of the walking time that the car alternative was often disadvantageous compared to the AV alternatives. To avoid this in the final experiments, it was decided to enlarge the range of the in-vehicle travel time and to lessen the range of the walking time.

- Adjustment 2: Attribute levels in-vehicle travel time [20, 30 40] → Attribute levels in-vehicle time [15, 30, 45]
- Adjustment 3: Attribute levels walking time [3, 6, 9] → Attribute levels walking time [2, 4, 6]

In the first version of the final survey it was explained that every hour extra work was directly compensated with an hourly salary. However, respondents mentioned that this does not happen occasionally. So, in the description it is mentioned that the extra working time means generating more income or spare time.

- Adjustment 4: Explanation that 'work extra time' implies only additional income → Explanation that 'work extra time' implies either additional income or spare time.

Respondents noted that it makes a big difference if one travels alone or accompanied. In the case of travelling alone it is more likely that one performs working activities than travelling with companions. Since the focus of research is on private vehicles, it is assumed that if one travels accompanied that it has been with relatives or acquaintances. The attribute is 'travel company' is added with the attribute levels 'travel alone' and 'travel with family/friends'.

- Adjustment 5: Add the attribute 'company' with attribute levels [travel alone, travel with family/friends]

5.2.2 FINAL EXPERIMENTS

This last subsection provides an example of how the final experiments look like. Both (AV & chauffeur-driven car) experiments are distributed using two separate Internet panels to reduce bias as much as possible. The final surveys were distributed through Dutch Internet panels. The AV-survey was distributed through respondentendatabase.nl and the chauffeur-survey was distributed making use of globaltestmarket.com. Respondents got paid to complete the survey. TNO funded the survey.

The software package NGENE (ChoiceMetrics, 2014) has been used to construct the D-efficient designs. Effect coding is used for the activity attribute and the travel company attribute. The coding for the activity attribute levels is +1 for working extra time and save time at the office is set on -1. Regarding the travel company travelling alone is fixed on -1, whereas travelling with family/friends is fixed on +1.

The output of NGENE were 12 choice tasks with a D-error of 0.051001. After the design generation some adjustments are made to avoid dominance of an alternative in the choice tasks. As mentioned earlier the two AV types will be explained before starting the choice tasks. These descriptions included images of how an AV could look like in the future. The images that are used are shown in Figure 5.1 and Figure 5.2.

Figure 5.1: Image used in the final survey as possible AV-leisure interior.

Figure 5.2: Image used in the final survey as possible AV-office interior.

The outline of the final survey is as follows:

- Introducing text
- Part I: 12 Choice tasks
- Part II: Rating 18 attitudinal statements
- Part III: Questions regarding socio-economic data
- Closure and thanking the respondents

An example of a choice task of the AV-case is shown in Figure 5.3. The final surveys can be found in Appendix B.

EXAMPLE:
Assume your next trip is a trip from home to work, which option would you choose to perform that next trip?

A. Conventional car	B. AV – office interior	C. AV – leisure interior
Travel time: 15 Min	Travel time: 45 Min	Travel time: 30 Min
Travel costs: € 4.50	Travel costs: € 4.50	Travel costs: € 7.50
Walking time: 6 Min	Walking time: 0 Min	Walking time: 0 Min
AV activity: driving	AV activity: working extra time	AV activity: do whatever you want
Travel companions: friends and/or family	Travel companions: friends or family	Travel companions: alone

Figure 5.3: Example of a choice task – final survey AV-case.

This chapter included the results of the prior-estimation survey and the outline of the final surveys. The prior-estimation study resulted in priors that are used for the experimental design of the final survey. Secondly, with feedback from the respondents, some adjustments were made in the final surveys. The last part of this chapter provided information on what images were used as example of the AV interiors, and an example of a choice task was given.

6 SAMPLES DESCRIPTIVES

After collecting the data it is of high importance to check whether the data is useful and if the sample represents the population. Two national online panels in the Netherlands are used for gathering respondents for the designed online questionnaires. This has been done to reduce the bias between the experiments. Each panel is used for answering one surveys. Firstly the data of the respondents that filled in the AV-survey is checked. Then, in subsection 6.2 the data of the respondents that filled in the chauffeur-case is described.

6.1 DESCRIPTIVE STATISTICS AV-CASE

Only people who were in possession of a driving license were allowed to fill in the survey. The online panel distributors took care that the share male-female was approximately equal. It was the purpose to represent the Dutch population as much as possible regarding several socio-economic variables like gender, age, educational level and employment.

The minimal number of respondents needed for the discrete choice modelling is determined with Equation 22 as described by (Johnson & Orme, 2003; Orme, 1998).

Equation 22

$$N = 500 * \frac{C}{T * A} = 500 * \frac{3}{12 * 3} = 41.7 = 42$$

Where N is the minimum required respondents, C equals the largest number of levels for any of the attributes, T equals the number of choice tasks and A is the number of alternatives.

6.1.1 COMPARISON SAMPLE AND POPULATION REGARDING SOCIO-ECONOMIC VARIABLES AV-CASE

In total 279 persons started the survey, of which 252 (90.3%) completed all questions. It is checked whether respondents filled in 18 times the same answers on the statements (e.g. all statements rated with a 7). No respondents were excluded due to this criterion. At the end, a total of 252 * 12 = 3,024 choices are observed. Enough respondents are collected for conducting the discrete choice modelling.

Table 6.1 provides an overview of the comparison between the respondents of the AV-case and the Dutch population. The male population is slightly oversampled while the female population is the opposite (CBS Statline, 2016c). However, the difference of 2.5 percentage is very small. Since, only people older than 18 years were allowed to fill in the survey, age categories starting from 20 years are compared in this experiment. One respondent was 18 years old. This respondent is added to the age category 20-39 years. The age categories 50 to 59 and 60 to 69 are oversampled compared to the population (CBS Statline, 2016a). Especially the discrepancy in the age group 50+ is large. The sample includes no respondents older than 70 year. It could be that elderly people are less frequent users of the Internet and therefor the online survey was less accessible for them.

The sample is representative for the population regarding the educational level (CBS Statline, 2016b), however, the sum of higher education people is overrepresented. The respondents that only completed the primary school are a little underrepresented.

Table 6.1: Comparison between full sample (AV-case) and Dutch population for different socio-demographic variables.

Socio-economic variable	*Category*	*Share sample*	*Share population*	*Difference*
Gender	Male	52.0%	49.5%	2.5 per cent point
	Female	48.0%	50.5%	-2.5 per cent point
Age	20 to 29	12.7%	16.2%	-3.5 per cent point
	30 to 39	11.9%	15.4%	-3.5 per cent point
	40 to 49	18.3%	18.3%	-
	50 to 59	29.0%	18.6%	10.4 per cent point
	60 to 69	28.2%	16.0%	12.2 per cent point
	≥ 70	0.0%	15.5%	-15.5 per cent point
Educational level	Primary school	3.2%	9.9%	-6.7 per cent point
	Lower vocational/secondary education	21.0%	21.0%	-
	Higher/intermediate/pre-university education	41.7%	41.0%	0.7 per cent point
	Higher vocational education	29.4%	17.9%	11.5 per cent point
	University	4.4%	10.1%	-5.7 per cent point
	None	0.4%	-	-
Employment	Full-time job	36.9%	33.9%	3.0 per cent point
	Part-time job	19.8%	31.9%	-12.1 per cent point
	Student	4.8%	5.7%	-0.9 per cent point
	Retired	7.9%	24.3%	-16.4 per cent point
	Other	30.6%	4.2%	26.4 per cent point

The sample has similarities with the population regarding employment status (CBS, 2013, 2015c, CBS Statline, 2017a, 2017b, DUO, 2017a, 2017b). The share of students and the full-time (FT) workers are equals almost the population. The retired respondents and the part-time (PT) workers are underrepresented in the sample. An explanation for the underrepresentation of the retired respondents is in accordance with the argument provided by the elderly people; less frequent Internet visitors. The share of 'other' employed respondents is high in the sample, what can be explained by the fact that people got a financial incentive to fill in the survey. Jobless people are included in this category and it is imaginable that this group is more sensitive for the financial compensation of filling in a survey. Eventually, it is concluded that this sample represents the Dutch population well enough.

6.1.2 NON-TRADER ANALYSIS AV-CASE

Besides validating whether the sample is representative for the population a so-called non-trader analysis will be conducted. The non-trader principle refers to that a respondent always chooses the same alternative in every choice tasks. This phenomenon occurs most likely in the case of labelled alternatives, which is the case in this study. Three explanations are given for this behaviour. Firstly, non-trading may reflect the presence of an extreme preference for one mode of transport. Secondly, respondents do not take the survey seriously, or he or she gets bored. The third explanation is that a respondent chooses politically or strategically. It is almost impossible to distinguish the three causes of non-trading behaviour. Non-trading behaviour impacts mainly the alternative-specific constants and inertia terms. It influences other marginal utility coefficients and willingness-to-pay indicators as well. This arises whenever the model is not able to explain all of the non-trading on the basis of constants (Hess et al., 2010).

The AV-case dataset includes 252 respondents from which 74 (29.4%) showed non-trading behaviour. From the non-traders, 53 respondents (71.6%) chose only the conventional car, 8 (10.8%) respondents chose only the A-office, and the remaining 13 (17.6%) respondents opted the

AV-leisure. The socio-economic characteristics of the non-traders are shown in Table 6.2. It reads that 31 males are non-traders. This is 23.7% of the total males of the AV-dataset. Next, 22 of the male non-traders opted always the conventional car. This means that 71.0% of the male non-traders chose always the conventional car.

It is striking that of the car non-traders 79.2% is older than 50 years old. Given the large amount of car non-traders and their older age, it appears that people with this age category prefer more the conventional car.

Table 6.2: Socio-demographic characteristics non-traders (AV-case).

Gender	*Male*	*Female*			
Total non-traders	31 (23.7%)	43 (35.5%)			
Always car	22 (71.0%)	31 (72.1%)			
Always AV-office	3 (9.7%)	5 (11.6%)			
Always AV-leisure	6 (19.4%)	7 (16.3%)			
Share sample excl. non-traders	47.9%	52.1%			
Share population	49.5%	50.5%			
Employment	*Work FT*	*Work PT*	*Student*	*Retired*	*Other*
Total non-traders	18 (19.4%)	11 (22.0%)	1 (8.3%)	9 (45.0%)	35 (45.5%)
Always car	11 (61.1%)	6 (54.5%)	1 (100.0%)	8 (88.9%)	27 (77.1%)
Always AV-office	4 (22.2%)	1 (9.1%)	0 (0.0%)	1 (11.1%)	2 (5.7%)
Always AV-leisure	3 (16.7%)	4 (36.4%)	0 (0.0%)	0 (0.0%)	6 (17.1%)
Share sample excl. non-traders	42.1%	21.9%	6.2%	6.2%	23.6%
Share population	33.9%	31.9%	5.7%	24.3%	4.2%
Age	*20-29*	*30-39*	*40-49*	*50-59*	*≥60*
Total non-traders	5 (15.6%)	7 (23.3%)	8 (17.4%)	25 (34.2%)	29 (40.8%)
Always car	4 (80.0%)	2 (28.6%)	5 (62.5%)	20 (80.0%)	22 (75.9%)
Always AV-office	0 (0.0%)	3 (42.9%)	1 (12.5%)	1 (4.0%)	3 (10.3%)
Always AV-leisure	1 (20.0%)	2 (28.6%)	2 (25.0%)	4 (16.0%)	4 (13.8%)
Share sample excl. non-traders	15.2%	12.9%	21.3%	27.0%	23.6%
Share population	16.2%	15.4%	18.3%	18.6%	31.5%
Educational level	*Primary school*	*Lower vocational/secondary education*	*Higher/intermed./pre-university education*	*Higher vocational education*	*University*
Total non-traders	6 (66.7%)	24 (45.3%)	29 (27.6%)	14 (18.9%)	1 (9.1%)
Always car	5 (83.3%)	17 (70.8%)	21 (72.4%)	9 (64.3%)	1 (100.0%)
Always AV-office	0 (0.0%)	2 (8.3%)	4 (13.8%)	2 (14.3%)	0 (0.0%)
Always AV-leisure	1 (16.7%)	5 (20.8%)	4 (13.8%)	3 (21.4%)	0 (0.0%)
Share sample excl. non-traders	1.7%	16.3%	42.7%	33.7%	5.6%
Share population	9.9%	21.0%	41.0%	17.9%	10.1%

Another observation is that 45.0% of the retired respondents are non-traders, whereas 88.9% of the retired non-traders opted always the conventional car. This could indicate that retirees have a preference for the conventional car. Furthermore, 45.5% of the respondents who indicate their employment as 'other' chose always the same alternative. In this group, 77.1% opted always the conventional car. The share of students, full-time (FT) workers and part-time (PT) workers that are non-traders is below 25%. At last, it is observed that lower educated respondents show relatively more non-trading than the higher educated respondents.

These results showed us that lower educated respondents, older respondents, retired respondents and 'other' employed respondents are relatively more non-traders. In the case one is non-trading, almost 72% opted for the conventional car. We can conclude that the AV-case sample that excludes non-traders has still enough similarities with the Dutch population. The 178 remaining trading respondents fulfil the minimal respondents needed for the discrete choice modelling.

It is decided that the choice models will be estimated using two different datasets:

- Dataset AV-case with all traders and non-traders, and;
- Dataset AV-case with only the traders.

6.2 DESCRIPTIVE STATISTICS CHAUFFEUR-CASE

The second part of this section is dedicated to the descriptive statistics of the respondents who completed the chauffeur-case survey.

6.2.1 COMPARISON SAMPLE AND POPULATION REGARDING SOCIO-ECONOMIC VARIABLES CHAUFFEUR-CASE

In total 301 respondents started the survey, from which 250 respondents completed the questionnaire (83.1%). Just as in the previous dataset, it is checked if respondents filled in the same rating for every attitudinal statement. Eight respondents rated all the statements the same or rated 17 out of 18 statements the same, and are excluded from further analysis. 242 useful responses left providing us 242 * 12 = 2.904 observations. The 242 respondents are enough for conducting the discrete choice modelling. Table 6.3 provides the comparison between the sample and the population regarding different socio-demographic variables.

Table 6.3: Comparison between full sample (chauffeur-case) and Dutch population for different socio-demographic variables.

Socio-economic variable	*Category*	*Share sample*	*Share population*	*Difference*
Gender	Male	47.9%	49.5%	-1.6 per cent point
	Female	52.1%	50.5%	1.6 per cent point
Age	20 to 29	11.2%	16.2%	-4.0 per cent point
	30 to 39	18.6%	15.4%	3.2 per cent point
	40 to 49	25.6%	18.3%	7.3 per cent point
	50 to 59	24.0%	18.6%	6.4 per cent point
	60 to 69	16.9%	16.0%	0.9 per cent point
	≥ 70	3.7%	15.5%	-11.8 per cent point
Educational level	Primary school	3.5%	9.9%	-6.4 per cent point
	Lower vocational/secondary education	10.0%	21.0%	-11.0 per cent point
	Higher/intermediate/pre-university education	48.1%	41.0%	7.1 per cent point
	Higher vocational education	26.8%	17.9%	8.9 per cent point
	University	11.7%	10.1%	1.6 per cent point
	None	-	-	-
Employment	Full-time job	57.4%	33.9%	23.5 per cent point
	Part-time job	29.8%	31.9%	-2.1 per cent point
	Student	0.4%	5.7%	-5.3 per cent point
	Retired	6.6%	24.3%	-17.7 per cent point
	Other	5.8%	4.2%	1.6 per cent point

The male population is slightly underrepresented in comparison to the female population. Some age groups are under- and overrepresented. Especially the age category 70 years and older is underrepresented. An explanation could be that older people are less connected to the Internet, while this survey was distributed online. Nonetheless, the other age groups show less discrepancy, thus the sample is considered representative regarding age.

The educational level of the sample is in comparison to the population relatively high educated. The lower vocational/secondary educated population is most underrepresented, while the higher- and higher vocational educated population are overrepresented. It is concluded that regarding educational level the sample is not very representative. The comparison in employment status shows discrepancies as well. The *part-time job* category, *student* category and the *other* category are very representative. However, large discrepancies are observed in the *full-time working* and the *retired* category. The full-time workers are highly oversampled (+23.8 per cent point) and the retirees are highly underrepresented (-17.7 per cent point). Since retirees are mostly older people, it is again understandable that due to less Internet access this group is underrepresented. An explanation why full-time workers are overrepresented cannot be given. Ultimately, it is conclude that the sample is representative for the Dutch population, but there are some significant differences.

6.2.2 NON-TRADER ANALYSIS CHAUFFEUR-CASE

96 (39.7%) respondents filled in the same answer for every choice task. Table 6.4 shows the characteristics of the non-traders. It reads as follows: 46 males are non-traders, which is 39.7% of the male sample. 37 males opted always the conventional car, which is 80.4% of male non-traders.

86.6% of the non-trading respondents opted always for the conventional car. Respectively 11.3% and 2.1% of the non-trader chose the chauffeur-driven office car and the chauffeur-driven leisure car. More than half of the retired respondents are non-traders and 64.3% of the respondents that has the employment status ‘other’ are non-traders as well. The share of working non-traders is higher in the chauffeur-case than in the AV-case.

It is striking that almost half of the respondents in the age 40-59 are identified as non-traders. 54.0% of the respondents in the age category ≥60 are non-traders. Relatively many respondents with a low education show non-trading behaviour. Surprisingly, higher educated respondents show more non-trading behaviour in the chauffeur-case than in the AV-case.

Regarding the chauffeur-case, we conclude that older respondents, retired respondents, ‘other’ employed respondents and lower educated respondents are more often non-traders. In this study, the non-traders have a strong preference for the conventional car. All in all, the sample excluding non-traders is representative for the Dutch population. 146 trading respondents remain, which is large enough for conducting the discrete choice modelling.

All discrete choice models using the chauffeur-case will be estimated with two datasets, which are:

- Dataset chauffeur-case with all traders and non-traders, and;
- Dataset chauffeur-case with only the traders.

Table 6.4: Socio-demographic characteristics non-traders (chauffeur-case).

Gender	*Male*	*Female*			
Total non-traders	46 (39.7%)	50 (39.7%)			
Always car	37 (80.4%)	46 (92.0%)			
Always CH-office	8 (17.4%)	3 (6.0%)			
Always CH-leisure	1 (2.2%)	1 (2.0%)			
Share sample excl. non-traders	47.9%	52.1%			
Share population	49.5%	50.5%			
Employment	*Work FT*	*Work PT*	*Student*	*Retired*	*Other*
Total non-traders	47 (33.8%)	31 (43.1%)	0 (0.0%)	9 (56.3%)	9 (64.3%)
Always car	37 (78.7%)	30 (96.8%)	0 (- %)	7 (77.8%)	9 (100.0%)
Always CH-office	9 (19.1%)	1 (3.2%)	0 (- %)	1 (11.1%)	0 (0.0%)
Always CH-leisure	1 (2.1%)	0 (0.0%)	0 (- %)	1 (11.1%)	0 (0.0%)
Share sample excl. non-traders	63.0%	28.1%	0.7%	4.8%	3.4%
Share population	33.9%	31.9%	5.7%	24.3%	4.2%
Age	*20-29*	*30-39*	*40-49*	*50-59*	*≥60*
Total non-traders	4 (14.8%)	11 (24.4%)	29 (46.8%)	25 (43.1%)	27 (54.0%)
Always car	4 (100.0%)	7 (63.6%)	26 (89.7%)	22 (88.0%)	24 (88.9%)
Always CH-office	0 (0.0%)	3 (27.3%)	3 (10.3%)	3 (12.0%)	2 (7.4%)
Always CH-leisure	0 (0.0%)	1 (9.1%)	0 (0.0%)	0 (0.0%)	1 (3.7%)
Share sample excl. non-traders	15.8%	23.3%	22.6%	22.6%	15.8%
Share population	16.2%	15.4%	18.3%	18.6%	31.5%
Educational level	*Primary school*	*Lower vocational/secondary education*	*Higher/ intermed./pre-university education*	*Higher vocational education*	*University*
Total non-traders	6 (60.0%)	14 (51.9%)	43 (37.4%)	24 (38.1%)	9 (33.3%)
Always car	6 (100.0%)	13 (92.9%)	36 (83.7%)	21 (87.5%)	7 (77.8%)
Always CH-office	0 (0.0%)	1 (7.1%)	6 (14.0%)	2 (8.3%)	2 (22.2%)
Always CH-leisure	0 (0.0%)	0 (0.0%)	1 (2.3%)	1 (4.2%)	0 (0.0%)
Share sample excl. non-traders	2.7%	8.9%	49.3%	26.7%	12.3%
Share population	9.9%	21.0%	41.0%	17.9%	10.1%

This chapter showed the descriptive statistics of the datasets and included non-trader analyses. It was concluded that both full samples have enough similarities with the Dutch population, but that the AV-full sample fits the population better than the chauffeur-full sample. The two samples excluding non-traders are representative for the population as well. It was striking that the AV-case has less non-traders than the chauffeur-case despite the fact that is had more respondents. The characteristics of the non-traders from the AV-case dataset and the chauffeur-case dataset were quite similar. Mainly, respondents who were older, low educated, retired and/or 'other' employed showed non-trading behaviour. The share of (FT & PT) working respondents and higher educated respondents that showed non-trading behaviour was significantly higher in the chauffeur-case than in the AV-case. This explains why more non-traders are identified in the chauffeur-case. At last, it was decided to use four different datasets for the model estimations.

7 RESULTS HYBRID CHOICE MODELLING

Chapter 7 is devoted to present the results of this study. The first part consists of an explanation of how the exploratory factor analysis (EFA) has been set up (7.1). Then, the results of the latent variable model of the AV-case is showed (7.2), followed up by the estimated results of the latent variable model of the chauffeur-case (7.3). Subsequently paragraph 7.4 provides the results of the discrete choice models estimated using the AV-case data. Paragraph 7.5 shows the results of the discrete choice models using the chauffeur-case data. The chapter ends with a discussion of the results.

7.1 SETTING UP THE EXPLORATORY FACTOR ANALYSIS

Before executing the exploratory factor analysis, several choices have to be made. Henson & Roberts (2006) provide a list of steps that must be taken when executing an EFA. The first step is to determine the *matrix of associations*. A matrix of association describes the relationship between variables in a dataset. Examples of these matrices are correlation and variance/covariance matrices. Since most data analysis software use the correlation matrix as default matrix of associations, it was used in this study as well.

The second step is to determine the *method of factor extraction*. Two methods are commonly used: the principal components (PCA) and the principal axis factoring (PAF). The differences between the two methods involve the entries on the diagonal of the matrix of associations that is analysed. In the case of the correlation matrix PCA uses ones on the diagonal while PAF uses reliability estimates (Thompson & Daniel, 1996). Analysts discuss whether or not PCA can be called a factor analysis. Overall PCA focuses on summarising many variables into fewer components and the latent structures, while PAF concentrates only on the common variance among variables, thus on the latent factors (Henson & Roberts, 2006). For this study the PAF extraction was used.

The third choice regards the *limitation of the amount of factors*. Different rules exist, but two rules are mostly used: the Kaiser criterion and the scree plot. The Kaiser criterion implies that as long as a factor has an Eigenvalue greater than one it must be taken into account (Kaiser, 1960). The scree plot shows the Eigenvalues of all initial components. From the component the line flattens out, this particular component and all the remaining components are excluded from further analysis.

The last choice regards the *factor rotation and coefficient interpretation*. This part is already explained in subsection 3.3. For this factor analysis, the orthogonal rotation has been used.

7.2 RESULTS LATENT VARIABLE MODEL (AV-CASE)

After the above-mentioned steps the latent variable model has been constructed with the software package SPSS (IBM, n.d.). Before iterating to the final factor solution, two tests were conducted to check whether the obtained data is suitable for (exploratory) factor analysis. The Kaiser-Meyer-Olkin test and the Bartlett's test of sphericity (Bartlett, 1950; Dziuban & Shirkey, 1974) indicated that the data is suitable for EFA. Indicators with a communality lower than 0.25 or with factor loads lower than 0.50 were excluded from the analysis. Table 7.1 provides the results of the estimated latent variable. All iteration steps and test results of the EFA have been worked out in Appendix D.

Table 7.1: Estimation results of latent variable model (AV-case) (factor loads <0.30 are not shown).

		Factor 1	*Factor 2*	*Factor 3*
ST12	I am afraid that the automated vehicle will not be fully aware of what is happening around him.	0.793		
ST10	I am afraid that the automated vehicle will malfunction.	0.743		
ST13	I do not like it that I do not have control of how the automated car drives.	0.738		-0.332
ST11	I dislike the idea of automated driving.	0.710	-0.393	
ST17	I like it if automated vehicles can adapt routes due to congestion.		0.728	
ST7	I like it that I can delegate the driving to the automated driving system if I am due to certain circumstances not able to drive myself.		0.712	
ST8	I like it that the automated car produces fewer pollutant emissions.		0.640	
ST9	I like it that the car can park itself at cheaper parking spaces away from my destination.		0.624	
ST3	I trust that a computer can drive my car with no assistance from me.	-0.310		0.834
ST4	I would be comfortable entrusting the safety of a close family member to an automated vehicle.	-0.344		0.832
ST14	I think that the automated driving system provides me more safety compared to manually driving.	-0.310	0.314	0.587

Five indicators in Table 7.1 have multiple loadings on different factors. For these factors, the factor loading on one factor is high, while the loading on the other factor is low. Although it is undesirable, it is assumed not to provide any problems in further analyses, since a simple structure is maintained.

The results show a three-factor solution including 11 out of 18 variables. The first factor has mainly variables included that concern about the trust aspect of automated vehicles. Therefore the name of the factor is *trust in automated driving*. The second factor mainly includes variables that are about the conveniences of automated driving. The variables contain aspects as route adaptation, self-parking, and delegate the car to drive itself when the occupants are not able to do it themselves. It is chosen to name this factor *convenience of automated driving*. The last factor reflects the attitude towards the safety of automated driving. It includes three variables regarding the safety of computer driven cars and whether or not one trusts an AV to a close family member. For this reason the last factor is given the name *safety of automated driving*.

7.3 RESULTS LATENT VARIABLE MODEL (CHAUFFEUR-CASE)

The same software package has been used to fulfil the latent variable model with the chauffeur-case data set: SPSS (IBM, n.d.). The Kaiser-Meyer-Olkin test and the Bartlett's test of sphericity (Bartlett, 1950; Dziuban & Shirkey, 1974) were executed to test if the data was suitable for this type of analysis. The tests showed that the data was suitable to conduct an EFA. Multiple iterations are executed to provide a latent variable model with indicators having a higher communality than 0.25 and a factor loading of at least 0.50. The outcomes of the above-mentioned tests and the iterations steps are shown in Appendix K Table 7.2 shows the results of the final estimated latent variable model. This final model consists of three latent factors.

Table 7.2: Estimation results of latent variable model (chauffeur-case) (factor loads <0.30 are not shown).

		Factor 1	*Factor 2*	*Factor 3*
ST12	I am afraid that the automated vehicle will not be fully aware of what is happening around him.	0.851		
ST11	I dislike the idea of automated driving.	0.783	-0.304	
ST13	I do not like it that I do not have control of how the automated car drives.	0.759		
ST10	I am afraid that the automated vehicle will malfunction.	0.643		
ST15	I wish that automated vehicles were not around in the future.	0.573	-0.368	
ST8	I like it that the automated car produces fewer pollutant emissions.		0.766	
ST9	I like it that the car can park itself at cheaper parking spaces away from my destination.		0.765	
ST7	I like it that I can delegate the driving to the automated driving system if I am due to certain circumstances not able to drive myself.		0.705	0.308
ST17	I like it if automated vehicles can adapt routes due to congestion.		0.671	
ST3	I trust that a computer can drive my car with no assistance from me.	-0.312	0.323	0.805
ST4	I would be comfortable entrusting the safety of a close family member to an automated vehicle.	-0.357		0.802

Some of the indicators load double on multiple factors. Indicators 3, 4, 7, 11 and 15 have double loadings, however the one loading is very high and the other loading is very low (close to 0.30). So, for an exploratory factor analysis this is not assessed as problematic, because a simple structure is maintained again.

In total 11 of the 18 indicators are used to estimate three latent factors. The estimated results show many similarities with the estimated results of the latent variable model with the AV-case data. In both cases three factors are estimated, from which factor 2 includes the exact same indicator variables. The third factor now only consists of two indicators instead of three. Factor 1, on the other hand, consists of five indicator variables, from which indicator 15 was not in the former EFA. The additional variable in the first factor is in line with the other indicators. Because most of the indicators are the same as in the former EFA the same factors names are applied. The first factor is defined as *trust in automated driving*, the second factor is defined as *conveniences of automated driving*, and the last factor is called *safety of automated driving*.

7.4 RESULTS DISCRETE CHOICE MODEL (AV-CASE)

Eight different models were estimated using the full sample and the sample excluding non-traders. So, in total 16 models are estimated regarding the AV-case. The most important results of all models are discussed in this subsection. First the results of the estimated models using the full sample are discussed followed up by the discussion of the results of the estimated models using the sample excluding non-traders. Detailed descriptions of all the estimated model results can be found in the appendices E-J.

7.4.1 RESULTS FULL SAMPLE (AV-CASE)

Before describing the results, the used effect coding of the non-linear variables is shown to understand the outcomes. The used coding is shown in Table 7.3.

Table 7.3: Effect coding used for attribute levels of nominal variables. IV = indicator variable.

Socio-economic variable	**Category**	**IV 1**	**IV 2**	**IV 3**	**IV 4**	**IV 5**
Travel company	Alone	-1				
	Family/friends	1				
Activity in AV with office interior	Save time at office	-1				
	Work extra time	1				
Gender	Female	-1				
	Male	1				
Car ownership	Yes	-1				
	No	1				
Able to work in AV	Yes	-1				
	No	1				
Willing to work in AV	Yes	-1				
	No	1				
Willing to buy an AV	Yes	-1				
	No	1				
Age	<26	-1	-1			
	26-60	0	1			
	>60	1	0			
Daily occupation	Work full-time	-1	-1	-1	-1	
	Work part-time	0	0	0	1	
	Student	0	0	1	0	
	Retired	0	1	0	0	
	Other	1	0	0	0	
Commonly used mode	Car	-1	-1	-1	-1	-1
	Car-pool	0	0	0	0	1
	Train	0	0	0	1	0
	BMT	0	0	1	0	0
	Bike	0	1	0	0	0
	None	1	0	0	0	0

As mentioned, per dataset six different models are estimated. These models are a base multinomial logit (MNL) model, an extended MNL model, a nested logit (NL) model, an error-component mixed logit (ML) model, a taste ML model and a combined ML model. The base MNL model includes only the SP attributes, whereas the extended MNL model includes socio-economic variables and the attitudinal latent factors as well. The NL model tests if alternatives are correlated with each other. The error-component model tests whether heterogeneity within the unobserved preference for AVs exists, while the taste ML model tests if heterogeneity exists within the mode-specific travel time parameters. The ML models correct for panel effects as well. All parameters in the ML models follow a normal distribution due to time constraints. One model run took around 10-12 hours.

Table 7.4: Model fit AV-case (full sample) models.

Model	*# of parameters*	*Adj. Rho-Square*	*Final LL*	*LRS*
Null	0	-	-3322.204	-
MNL base	11	0.08	-3043.778	556.852
MNL extended	19	0.207	-2614.156	1416.094
NL	20	0.212	-2596.994	1450.419
ML error-component	20	0.304	-2292.593	2059.22
ML taste	22	0.367	-2081.915	2480.577
ML combined	23	0.369	-2072.66	2499.087

The likelihood ratio test (LRS) is used to check whether an extended model actually fits the data better and not only having a higher adjusted Rho-Square due to additional parameters. The Chi-square distribution table is used to determine if the improvement of the model fit is statistically certain. Figure 7.1 shows the minimal needed LRS values for different significance levels, whereas df represents the degree of freedom.

Critical Values of the χ^2 Distribution

df \ p	0.995	0.975	0.9	0.5	0.1	0.05	0.025	0.01	0.005	df
1	.000	.000	0.016	0.455	2.706	3.841	5.024	6.635	7.879	1
2	0.010	0.051	0.211	1.386	4.605	5.991	7.378	9.210	10.597	2
3	0.072	0.216	0.584	2.366	6.251	7.815	9.348	11.345	12.838	3
4	0.207	0.484	1.064	3.357	7.779	9.488	11.143	13.277	14.860	4
5	0.412	0.831	1.610	4.351	9.236	11.070	12.832	15.086	16.750	5
6	0.676	1.237	2.204	5.348	10.645	12.592	14.449	16.812	18.548	6
7	0.989	1.690	2.833	6.346	12.017	14.067	16.013	18.475	20.278	7
8	1.344	2.180	3.490	7.344	13.362	15.507	17.535	20.090	21.955	8
9	1.735	2.700	4.168	8.343	14.684	16.919	19.023	21.666	23.589	9
10	2.156	3.247	4.865	9.342	15.987	18.307	20.483	23.209	25.188	10
11	2.603	3.816	5.578	10.341	17.275	19.675	21.920	24.725	26.757	11
12	3.074	4.404	6.304	11.340	18.549	21.026	23.337	26.217	28.300	12
13	3.565	5.009	7.042	12.340	19.812	22.362	24.736	27.688	29.819	13
14	4.075	5.629	7.790	13.339	21.064	23.685	26.119	29.141	31.319	14
15	4.601	6.262	8.547	14.339	22.307	24.996	27.488	30.578	32.801	15

Figure 7.1: Chi-square distribution table.

Table 7.4 shows the model fit of the AV-case models. All extended models are a significant improvement compared to the null model, which assumes that all variables equal zero. The LRS of the MNL base is calculated according Equation 23.

Equation 23

$$\mathrm{LRS} = -2 * (\mathrm{LL_{null}} - \mathrm{LL_{MNL\ base}}) = -2 * (-3322.204 - -3043.778) = 556.852$$

Furthermore it is computed whether each model is a statistical improvement compared to the previous model. Equations 24 to 28 show that each model does fit significantly better than the previous estimated model. Ultimately, the combined ML model fits the data best.

Equation 24

$$\mathrm{LRS} = -2 * (\mathrm{LL_{MNL\ base}} - \mathrm{LL_{MNL\ ext.}}) = -2 * (-3043.778 - -2614.156) = 859.24$$

Equation 25

$$\mathrm{LRS} = -2 * (\mathrm{LL_{MNL\ ext.}} - \mathrm{LL_{NL}}) = -2 * (-2614.156 - -2596.994) = 34.32$$

Equation 26

$$\mathrm{LRS} = -2 * \left(\mathrm{LL_{NL}} - \mathrm{LL_{ML\ error-comp.}}\right) = -2 * (-2596.994 - -2292.593) = 608.80$$

Equation 27

$$\mathrm{LRS} = -2 * \left(\mathrm{LL_{ML\ error-comp}} - \mathrm{LL_{ML\ taste}}\right) = -2 * (-2292.593 - -2081.915) = 421.36$$

Equation 28

$$\mathrm{LRS} = -2 * (\mathrm{LL_{ML\ taste}} - \mathrm{LL_{ML\ combined}}) = -2 * (-2081.915 - -2072.660) = 18.51$$

Table 7.5 shows the estimation results of the AV-case models, where the value between brackets is the t-value. Only the estimation results of the extended MNL are shown, since this model fits the data better compared to the MNL that includes only the SP attributes.

Before estimating the final extended MNL model, first all socio-economic variables and attitudinal factors were included in the model. Then, after the first model estimation, the insignificant parameters were left out the final model and the model was estimated again. Another important note is that the extended MNL model has been used as base model for the NL model and the ML models.

Table 7.5: Estimation results of the AV-case models (full sample).

Parameter	*MNL*	*NL*	*Error-component ML*	*Taste ML*	*Combined ML*
Constant_car	0.00	0.00	0.00	0.00	0.00
Constant_AV	0.76 (1.47)*	0.45 (1.22)*	-0.32 (-0.47)*	1.31 (1.81)*	1.07 (1.41)*
σ_constant_AV	-	-	-2.23 (-12.84)	-	1.61 (6.53)
Nest_parameter	-	1.63 (4.41)	-	-	-
Traveltime_AVL	-0.045 (-9.21)	-0.037 (-8.76)	-0.063 (-11.02)	-0.10 (-11.32)	-0.094 (-11.11)
Traveltime_AVO	-0.030 (-6.19)	-0.021 (-5.27)	-0.036 (-7.07)	-0.074 (-9.04)	-0.072 (-8.90)
Traveltime_car	-0.038 (-7.98)	-0.028 (-7.10)	-0.065 (-10.52)	-0.061 (-7.60)	-0.065 (-8.33)
σ_traveltime_AVL	-	-	-	0.065 (-11.31)	0.062 (-8.92)
σ_traveltime_AVO	-	-	-	0.053 (9.70)	0.050 (-8.77)
σ_traveltime_car	-	-	-	0.066 (9.67)	0.053 (-7.47)
Travelcosts_AVL	-0.28 (-9.68)	-0.26 (-9.79)	-0.30 (-10.04)	-0.49 (-12.44)	-0.49 (-12.25)
Travelcosts_AVO	-0.39 (-12.83)	-0.31 (-11.49)	-0.47 (-14.14)	-0.64 (-15.49)	-0.64 (-15.44)
Travelcosts_car	-0.26 (-4.96)	-0.23 (-5.64)	-0.49 (-7.14)	-0.44 (-6.07)	-0.48 (-6.39)
Activity_AVO	-0.11 (-2.23)	-0.050 (-1.21)*	-0.18 (-3.28)	-0.20 (-3.02)	-0.22 (-3.25)
Travel_company_AV	-0.10 (-3.37)	-0.12 (-4.55)	-0.052 (-1.63)*	-0.11 (-2.77)	-0.097 (-2.51)
Travel_company_car	-0.19 (-3.10)	-0.14 (-3.02)	-0.29 (-3.81)	-0.22 (-2.63)	-0.25 (-2.98)
Walkingtime_car	0.052 (1.62)*	0.018 (0.69)*	0.090 (2.29)	0.036 (0.83)*	0.044 (0.99)*
AbleToWork_car	0.13 (2.32)	0.11 (2.94)	0.26 (1.37)*	0.18 (1.21)*	0.21 (1.04)*
WillingToWork_car	0.32 (5.16)	0.24 (5.14)	0.47 (2.11)	0.29 (1.59)*	0.35 (1.44)*
Buy-AV_car	0.37 (5.90)	0.27 (5.58)	0.57 (2.40)	0.56 (2.97)	0.68 (2.77)
Convenience_car	-0.72 (-11.61)	-0.53 (-9.59)	-1.43 (-5.99)	-1.35 (-7.07)	-1.54 (-5.78)
Safety_car	-0.30 (-5.45)	-0.20 (-4.82)	-0.60 (-2.97)	-0.62 (-3.95)	-0.71 (-3.37)
Trust_car	0.25 (4.60)	0.17 (4.41)	0.47 (2.43)	0.36 (2.46)	0.43 (2.11)
Mode_BMT_car	1.04 (5.28)	0.75 (5.12)	1.69 (2.41)	1.04 (1.75)*	1.29 (1.42)*
Mode_carpool_car	-1.73 (-7.10)	-1.28 (-6.75)	-2.81 (3.25)	-1.80 (-2.49)	-2.27 (-2.11)
Adj. Rho-Square	0.207	0.212	0.304	0.367	0.369

** = not significant in a 95% confidence interval. AVO = AV-office, AVL = AV-leisure.*

Nest parameter Three different NL models were estimated, from which one NL model showed a significant nest parameter. In this NL model the AV-office alternative and the conventional car alternative belonged to the same nest. The AV-office and the AV-leisure, and the AV-leisure and the conventional car belong not to the same nest. The results imply that only commonalities are experienced between the conventional car and the AV-office car. This result was not according expectation, therefore it is further discussed in paragraph 7.6 (discussion).

Standard deviations In all models no mean preference has been observed for AVs, but heterogeneity in the unobserved preference for AVs is measured according the ML models. It is also found that heterogeneity exists in the mode-specific time parameters and thus in the VOTTs.

Travel time All mean travel time parameters are valued negatively (unit: utile/min), which means that an increase in travel time indicates an increase in disutility regarding the mode used. In most models AV-leisure travellers are more sensitive for a travel time increase compared to car travellers and AV-office travellers.

Travel costs Overall, it is indicated that AV-office users are most sensible to an increase in travel costs (unit: utile/€) in comparison to car users and AV-leisure users, which implies that people do not want to pay to work in a vehicle. The valuation of an increase in travel costs is almost equal for AV-leisure travellers and car users. Only the error-component ML model shows big differences between these mean parameters values.

Travel company & activity All models show a negative parameter value regarding activity in the AV-office. This indicates that, due to the effect coding, substituting travel time for time at home is preferred over working additional time. However, the NL model estimated an insignificant parameter for *Activity*_AVO. Also all travel company parameters, regardless of the mode, show a negative value. This means that travelling alone is preferred over travelling with family/friends.

Walking time The walking time is only significant in the error-component model and shows a positive value. This outcome is very odd, and therefore discussed in paragraph 7.6 (discussion).

Socio-economic factors The positive valuation of *Buy-AV_car* indicates that if one is not willing to buy an AV for the same price as a conventional car, he or she has a preference for the car. The same behaviour is indicated if one is not able to work in a car without trepidation and high comfort, and if one is not willing to work in an AV, although not all models indicate these parameters significant.

In all models the car-pooling parameter shows a negative sign, which indicates that car-poolers have a preference for automated driving over conventional car driving. Three models indicate a positive attitude (positive valuations) of bus/tram/metro users towards the conventional car with respect to the AV options. All models indicate that full-time workers have a preference for the conventional car.

Attitudinal factors At last, the importance of attitudinal factors regarding choice behaviour have been proved by these models as had been by Yap et al. (2016). The three identified attitudinal factors are significant in all models. The *Convenience_car* parameter that measures the conveniences of automated driving is valued negatively, which means that if a respondent has a positive attitude towards the conveniences of automated driving, he or she prefers the AV options. This attitudinal factor influences mostly the choice behaviour, since its utility value is about 2.3 times larger than the safety factor and about 3.2 times higher than the trust factor. The same observation is measured regarding a positive attitude towards the safety of automated driving (*Safety_car*). Regarding relative importance is the safety attitudinal factors ranked second. The ratio of the average parameter value of the factor safety and the average value of the factor trust is 1.4. Considering the positive parameter values of T*rust_car*, the model results indicate that if one does not trust an AV, one prefers a conventional car. Having trust or not in automated driving influences the choice behaviour least.

VOTT It is assumed that all mode-specific travel time parameters and mode-specific travel costs parameters are linear. In this case, the VOTT calculation is the ratio of the time and costs parameters. Regarding the taste ML and combined ML model this calculation is a bit different. Because the travel time parameters are normally distributed, the VOTT is normally distributed as well. The distribution is calculated as follows (Hess, Bierlaire, & Polak, 2004; Sillano & de Dios Ortuzar, 2005):

Equation 29

$$\left.\begin{array}{c}\beta_{TT} \sim \mathrm{N}(\mu_{TT}, \sigma_{TT}) \\ \beta_{TC} \text{ fixed}\end{array}\right\} \frac{\beta_{TT}}{\beta_{TC}} \sim \mathrm{N}\left(\frac{\mu_{TT}}{\beta_{TC}}, \frac{\sigma_{TT}}{\beta_{TC}}\right)$$

The VOTT estimations are shown in Table 7.6. The results indicate that the mean VOTT estimate for AV-office users is always the lowest compared to the VOTT estimates of car travellers and AV-leisure travellers. However, the MNL model indicates that the mean VOTT is highest for conventional car users, while the NL model and the ML models tell us that the mean VOTT estimate of AV-leisure users is highest compared to the rest.

Table 7.6: Mean VOTT estimates and standard deviations AV-case in [€/hour] (full sample).

	MNL	*NL*	*Error-component ML*	*Taste ML*	*Combined ML*
Mean VOTT car	8.77	7.24	8.77	8.23	8.14
Sigma VOTT car	-	-	-	8.95	6.56
Mean VOTT AVO	4.61	4.12	4.61	6.94	6.76
Sigma VOTT AVO	-	-	-	5.04	4.64
Mean VOTT AVL	7.91	8.75	9.54	12.15	11.58
Sigma VOTT AVL	-	-	-	7.85	7.59

The standard deviation of the VOTT of conventional car users in the taste ML model (8.95) is bigger than its mean value. The results show a big switch in mean VOTT for AV-office users between the error-component ML (4.61) and the taste ML model (6.94). The same observation is done regarding the VOTT of the AV-leisure users: from 7.91 (MNL) to 11.58 (combined ML).

For the models that provide the VOTT estimate as the ratio of time and costs (MNL, NL and error-component ML) it is tested whether the found values are significantly different from zero and whether the found values differ significantly from each other. To determine if the ratios are significantly different from zero, the Delta method has been applied (Cranenburgh & Chorus, 2013; Daly et al., 2012). To test whether the VOTT estimations differ significantly from each other, an adaption of Welch's t-test has been used (Welch, 1938).

Table 7.7: Delta method and Welch's t-test results VOTT ratios AV-case (full sample).

	MNL	*NL*	*Error-component ML*
Delta-method results			
Mean VOTT car	6.03	6.53	9.00
Mean VOTT AVO	5.98	4.97	6.33
Mean VOTT AVL	6.85	6.26	7.71
Welch's t-test			
VOTT car – VOTT AVO	2.49	2.26	3.04
VOTT car – VOTT AVL	0.38*	0.85*	2.38
VOTT AVO – VOTT AVL	3.04	2.85	4.50

** = not significant in a 95% confidence interval.*

Table 7.7 shows the t-values of the found VOTT estimates. It indicates that all ratios are significant. Welch's t-test indicated that the mean VOTT estimates of AV-leisure users and car users found estimated with the MNL model and the NL model do not differ significantly from each other. All other ratios do differ significantly from one another.

As mentioned in subsection 3.2.3 the use of a normal distribution has a serious downside, since it allows the travel time parameter to be positive. A positive travel time parameter leads to a negative VOTT estimation, which is odd. The taste ML model and the combined ML model both have the probability of estimating a positive time parameter for an individual.

The results showed that a substantial part of the probability density of the car-specific travel time parameter has a positive value. The results showed that a considerable part of the probability density of the AV-office-specific travel time parameter and the AV-leisure-specific time parameter has a positive value as well.

It is observed that a certain probability exists that a positive travel time parameter could be estimated for an individual. The use of the simple ratio of the means could lead to a loss of information concerning the distribution of the VOTT across the population. For that reason a calculation of the variance for the ratio of coefficients is calculated (Hess et al., 2004). Table 7.8 shows the 95% quantile intervals of the VOTT estimates. It shows that ignoring this spread in values leads to an important loss of information. The table does indicate that the spread in VOTT is smaller for the parameters estimated with the combined ML model.

Table 7.8: 95% quantile intervals for the distribution of the VOTTs in [€/hour] (full sample).

	Taste ML Lower 95% quantile limit	*Taste ML Upper 95% quantile limit*	*Combined ML Lower 95% quantile limit*	*Combined ML Upper 95% quantile limit*
β_{TT_CAR}	-9.31	25.78	-4.73	21.00
$\beta_{TT\_AV\text{-}OFFICE}$	-2.93	16.82	-2.33	15.84
$\beta_{TT\_AV\text{-}LEISURE}$	-3.23	27.52	-3.29	26.45

This subsection briefly discussed the most important results of the estimated models using the full sample of the AV-case. Next, the results of the models estimated on the sample excluding non-traders are described.

7.4.2 RESULTS SAMPLE EXCLUDING NON-TRADERS (AV-CASE)

The same six models are estimated with this dataset as with the full sample. Again, the selected parameters in the ML models are normally distributed, where the models estimate the mean parameter values and the corresponding standard deviations. It must be noted that the extended MNL model is used as base model for the NL model, error-component ML model, taste ML model and combined ML model. The ML models correct for panel effects.

Table 7.9: Model fit AV-case (excl. non-traders) models.

Model	*# of parameters*	*Adj. Rho-Square*	*Final LL*	*LRS*
Null	0	-	-2346.636	-
MNL base	11	0.12	-2053.66	585.952
MNL extended	19	0.155	-1964.63	764.011
NL	-	-	-	-
ML error-component	20	0.171	-1924.967	843.337
ML taste	22	0.199	-1857.04	979.191
ML combined	-	-	-	-

Table 7.9 shows the model fits of the estimated models. The LRS results below show that the model fit improves statistically with each model compared to the previous model.

Equation 30

$$\text{LRS} = -2 * (\text{LL}_{\text{MNL base}} - \text{LL}_{\text{MNL ext.}}) = -2 * (-2053.660 - -1964.630) = 178.06$$

Equation 31

$$\text{LRS} = -2 * \left(\text{LL}_{\text{MNL ext.}} - \text{LL}_{\text{ML error-comp.}}\right) = -2 * (-1964.630 - -1924.967) = 79.33$$

Equation 32

$$\text{LRS} = -2 * \left(\text{LL}_{\text{ML error-comp}} - \text{LL}_{\text{ML taste}}\right) = -2 * (-1924.967 - -1857.04) = 135.85$$

Table 7.10 provides the estimation results, where the t-values are shown between brackets. Only the values of the extended MNL are shown. The adjusted Rho-Squares show that the combined ML model fits the data best. However, in this model the mean preference for an AV and its corresponding standard deviation are not significant, thus a taste ML was estimated.

Table 7.10: Estimation results of AV-case models (excl. non-traders).

Parameter	*MNL*	*NL*	*Error-component ML*	*Taste ML*	*Combined ML*
Constant_car	0.00	0.00	0.00	0.00	0.00
Constant_AV	0.674 (1.07)*	0.674 (1.07)*	0.47 (0.70)*	1.27 (1.81)*	1.25 (1.76)*
σ_constant_AV	-	-	0.89 (9.49)	-	0.297 (0.85)*
Nest_parameter	-	1.26 (1.72)*	-	-	-
Traveltime_AVL	-0.063 (-11.02)	-0.063 (-11.02)	-0.070 (-11.48)	-0.084 (-11.45)	-0.084 (-11.46)
Traveltime_AVO	-0.041 (-7.25)	-0.041 (-7.25)	-0.043 (-7.46)	-0.062 (-8.59)	-0.062 (-8.57)
Traveltime_car	-0.056 (-9.67)	-0.056 (-9.67)	-0.064 (-10..22)	-0.065 (-9.44)	-0.065 (-9.47)
σ_traveltime_AVL	-	-	-	0.033 (9.00)	0.033 (8.57)
σ_traveltime_AVO	-	-	-	0.033 (8.53)	0.032 (8.08)
σ_traveltime_car	-	-	-	0.024 (5.64)	0.023 (4.70)
Travelcosts_AVL	-0.37 (-10.92)	-0.37 (-10.92)	-0.37 (-10.98)	-0.46 (-12.07)	-0.46 (-12.01)
Travelcosts_AVO	-0.50 (-14.45)	-0.50 (-14.45)	-0.52 (-14.77)	-0.59 (-15.09)	-0.60 (-15.10)
Travelcosts_car	-0.42 (-6.34)	-0.42 (-6.34)	-0.49 (-6.91)	-0.46 (-6.32)	-0.47 (-6.31)
Activity_AVO	-0.14 (-2.35)	-0.14 (-2.35)	-0.16 (-2.69)	-0.18 (-2.75)	-0.18 (-2.76)
Travel_company_AV	-0.092 (-2.70)	-0.092 (-2.70)	-0.076 (-2.20)	-0.11 (-2.86)	-0.11 (-2.82)
Travel_company_car	-0.23 (-3.17)	-0.23 (-3.17)	-0.27 (-3.44)	-0.23 (-2.87)	-0.23 (-2.87)
Walkingtime_car	0.029 (0.75)*	0.029 (0.75)*	0.045 (1.10)*	0.023 (0.55)*	0.024 (0.55)*
Age1_car	0.34 (3.01)	0.34 (3.01)	0.37 (1.98)	0.29 (1.53)*	0.28 (1.47)*
WillingToWork_car	0.29 (4.63)	0.29 (4.63)	0.33 (3.10)	0.29 (2.73)	0.30 (2.67)
Buy-AV_car	0.41 (6.11)	0.41 (6.11)	0.47 (4.11)	0.49 (4.24)	0.50 (4.24)
Convenience_car	-0.30 (-3.65)	-0.30 (-3.65)	-0.35 (-2.57)	-0.45 (-3.19)	-0.42 (-2.93)
DO_retired_car	-0.62 (-4.00)	-0.62 (-4.00)	-0.68 (-2.70)	-0.69 (-2.71)	-0.68 (-2.58)
DO_workpt_car	0.30 (2.66)	0.30 (2.66)	0.32 (1.76)*	0.33 (1.77)*	0.34 (1.78)*
Mode_BMT_car	0.85 (3.99)	0.85 (3.99)	0.98 (2.71)*	0.84 (2.27)	0.87 (2.30)
Mode_carpool_car	-1.45 (-5.23)	-1.45 (-5.23)	-1.64 (-3.54)	-1.47 (-3.09)	-1.51 (-3.10)
Adj. Rho-Square	0.155	0.155	0.171	0.199	0.200

** = not significant in a 95% confidence interval. AVO = AV-office, AVL = AV-leisure.*

Nest parameter Again, three NL models were estimated. However, in this case none of the nest parameters were estimated significantly, which means that the NL models transformed into a MNL model.

Standard deviations The model results indicate that no preference is observed for the AV alternatives, but heterogeneity in the unobserved preference for AV exists according the error-component ML model (significant sigma; 0.89). Heterogeneity exists in the travel time parameters as well, because the standard deviations of the mode-specific travel time parameters are significant.

Travel time According all models, an increase of one minute in travel time (unit: utile/min) causes least disutility when travelling in the AV-office. An increase in travel time is most negatively valued in the AV with leisure interior. These robust outcomes were not found when using the full sample.

Travel costs Regarding travel costs (unit: utile/€), all models indicate that an increase is most negatively experienced in the AV-office. A difference regarding the full-sample results is that all models indicate that people travelling with an AV-leisure are least sensitive to travel costs, and that people travelling with an AV-office are most sensitive to an increase in costs. This means that people do not want to pay to work in a car.

Travel company & activity The results of the AV-office activity parameter and the travel company parameters are in line with the results of the models using the full sample.

Socio-economic factors The *WillingToWork_car* and *Buy-AV_car* parameter results are in line with the models estimated using the full sample. The *AbleToWork_car* parameter is not estimated significantly. The MNL model and the error-component ML model indicate that people in the age category >60 have a preference for the conventional car (MNL: 0.34 for car, ECML: 0.37 for car), while respondents in the age category <26 prefer an AV (MNL: -0.34 for car, ECML: -0.37 for car). However, and maybe contradictory, retirees have an average preference for an AV seeing the negative coefficient in all models. Part-time workers (significant in the MNL model) have a preference for the normal car over the AV (0.30). Furthermore, all models indicate that full-time workers prefer a normal car as well over the AV options (example MNL: -.62 * -1 + 0.30 * -1 = 0.32 for car). Car-poolers, BMT users and current car users show the same behaviour as in the full sample models.

Attitudinal factors Ultimately, one attitudinal factor has been found significant. If one has a positive attitude towards the conveniences of automated driving, he or she has, seen the negative value, a preference for an AV.

Table 7.11: Mean VOTT estimates and standard deviations AV-case in [€/hour] (excl. non-traders).

	MNL	*NL*	*Error-component ML*	*Taste ML*	*Combined ML*
Mean VOTT car	7.91	7.91	7.83	8.37	8.37
Sigma VOTT car	-	-	-	3.08	3.08
Mean VOTT AVO	4.97	4.97	4.93	6.26	6.26
Sigma VOTT AVO	-	-	-	3.30	3.30
Mean VOTT AVL	10.47	10.47	11.24	10.82	10.82
Sigma VOTT AVL	-	-	-	4.26	4.26

VOTT The mean VOTT estimates with corresponding standard deviations are shown in Table 7.11. The results indicate that the mean VOTT for travellers with the AV with office interior is lower compared to conventional car travellers and AV-leisure travellers. The valuation of travel time is the highest when travelling with the AV-leisure with respect to the other travellers.

Compared to the results estimated using the full sample it is observed that the standard deviations are lower. Especially the sigma of the VOTT of conventional car improved. Furthermore, it is observed that the VOTT estimates are more stable per user group compared to the full sample results.

Again, the standard errors of the mean VOTT estimates of the MNL model and the error-component ML model are computed. It became clear that all ratios are significant, see Table 7.12. Next, after applying the adapted Welch's t-test, it came out that only the mean VOTT for car users and AV-leisure users do not differ significantly from each other when they are estimated with the MNL parameters. The mean VOTT estimates of the error-component ML model do differ significantly from each other. The results of the Welch's t-test are shown in Table 7.12 as well.

Table 7.12: Delta method and Welch's t-test results VOTT ratios AV-case (excl. non-traders).

	MNL	*NL*	*Error-component ML*
Delta-method results			
Mean VOTT car	8.00	8.00	8.78
Mean VOTT AVO	6.64	6.64	6.83
Mean VOTT AVL	8.18	8.18	8.39
Welch's t-test			
VOTT car – VOTT AVO	2.37	2.37	2.53
VOTT car – VOTT AVL	1.58*	1.58*	2.13
VOTT AVO – VOTT AVL	3.69	3.69	4.16

* = *not significant in a 95% confidence interval.*

As mentioned before, making use of the normal distribution causes positive values of the travel time parameter. The results showed that a small part of the probability densities of the travel time parameters have a positive value.

The VOTT distributions the 95% confidence quantile intervals are shown in Table 7.13. The results indicate that within the 95% confidence interval no negative VOTT occurs for conventional car travellers and AV-leisure travellers. The calculations show that a negative VOTT estimate is still possible for the AV-office travellers, but in a lesser extent than the full-sample VOTTs.

Table 7.13: 95% quantile intervals for the distribution of the VOTTs in [€/hour] (excl. non-traders).

	Taste ML *Lower 95% quantile limit*	*Taste ML* *Upper 95% quantile limit*
β_{TT_CAR}	2.33	14.42
$\beta_{TT\_AV\text{-}OFFICE}$	-0.21	12.74
$\beta_{TT\_AV\text{-}LEISURE}$	2.46	19.18

7.5 RESULTS DISCRETE CHOICE MODEL (CHAUFFEUR-CASE)

Regarding the chauffeur-case the same models are estimated as for the AV-case. For all models, the same effect coding, as provided in Table 7.3, has been used. Detailed descriptions of the model results can be found in the appendices K-Q.

7.5.1 RESULTS FULL SAMPLE (CHAUFFEUR-CASE)

The same process to estimate the final MNL model, NL model, and ML models as for the AV-case was applied to the chauffeur-case. The ML models are estimated with a normal distribution as well and correct for panel effects.

Table 7.14 provides an overview of the model fit of each model. It is concluded that all models fit the data significantly better than the null model.

Table 7.14: Model fit chauffeur-case (full sample) models.

Model	*# of parameters*	*Adj. Rho-Square*	*Final LL*	*LRS*
Null	0	-	-3189.271	-
MNL base	11	0.169	-2639.200	1100.143
MNL extended	21	0.289	-2248.704	1883.332
NL	22	0.292	-2237.021	1904.502
ML error-component	22	0.411	-1857.658	2663.227
ML taste	24	0.455	-1712.869	2952.806
ML combined	25	0.458	-1704.906	2968.731

The calculations of the LRS show that each model fits the data better than the previous model. The adjusted Rho-Square and the LRS tell us that the combined-ML model fits the data best.

Equation 33

$$\mathrm{LRS} = -2 * (\mathrm{LL}_{\mathrm{MNL\ base}} - \mathrm{LL}_{\mathrm{MNL\ ext.}}) = -2 * (-2639.200 - -2248.704) = 780.99$$

Equation 34

$$\mathrm{LRS} = -2 * (\mathrm{LL}_{\mathrm{MNL\ ext.}} - \mathrm{LL}_{\mathrm{NL}}) = -2 * (-2248.704 - -2237.021) = 23.37$$

Equation 35

$$\mathrm{LRS} = -2 * \left(\mathrm{LL}_{\mathrm{NL}} - \mathrm{LL}_{\mathrm{ML\ error-comp.}}\right) = -2 * (-2237.021 - -1857.658) = 758.73$$

Equation 36

$$\mathrm{LRS} = -2 * \left(\mathrm{LL}_{\mathrm{ML\ error-comp}} - \mathrm{LL}_{\mathrm{ML\ taste}}\right) = -2 * (-1857.658 - -1712.869) = 289.578$$

Equation 37

$$\mathrm{LRS} = -2 * (\mathrm{LL}_{\mathrm{ML\ taste}} - \mathrm{LL}_{\mathrm{ML\ combined}}) = -2 * (-1712.869 - -1704.906) = 15.93$$

Table 7.15 shows the estimation results of the estimated models using the full sample. The shown values of the MNL model are the parameter values of the extend MNL model.

Nest parameter Three NL models were estimated, from which two NL models did not estimate a significant nest parameter. It is found that only the CH-office and the conventional car belong to the same nest. No commonalities are observed between the CH-office and CH-leisure, and the CH-leisure and the conventional car.

Standard deviations No significant mean preference for chauffeur-driven cars is observed. However, heterogeneity exists within the preference for chauffeur-driven cars according the error-component ML model and the combined ML model. The standard deviations of the mode-specific travel time parameters are significant as well, which means that individual variety exists in the valuation of travel time.

Table 7.15: Estimation results of the chauffeur-case models (full sample).

Parameter	*MNL*	*NL*	*Error-component ML*	*Taste ML*	*Combined ML*
Constant_car	0.00	0.00	0.00	0.00	0.00
Constant_CH	0.77 (1.37)*	0.45 (1.07)	-0.95 (-0.97)*	1.38 (0.14)*	0.88 (0.80)*
σ_constant_CH	-	-	2.74 (12.51)	-	2.01 (4.68)
Nest_parameter	-	1.53 (3.76)	-	-	-
Traveltime_CHL	-0.044 (-7.90)	-0.037 (-7.49)	-0.072 (-10.43)	-0.11 (-10.96)	-0.11 (-10.56)
Traveltime_CHO	-0.030 (-5.03)	-0.020 (-4.23)	-0.040 (-6.21)	-0.077 (-7.73)	-0.077 (-7.83)
Traveltime_car	-0.030 (-5.85)	-0.021 (-5.23)	-0.060 (-8.84)	-0.040 (-3.81)	-0.054 (-5.04)
σ_traveltime_CHL	-	-	-	0.057 (8.77)	0.055 (8.50)
σ_traveltime_CHO	-	-	-	0.058 (8.51)	0.058 (9.10)
σ_traveltime_car	-	-	-	0.11 (10.62)	0.083 (6.63)
Travelcosts_CHL	-0.45 (-12.09)	-0.41 (-12.01)	-0.49 (-12.53)	-0.72 (-14.00)	-0.73 (-13.77)
Travelcosts_CHO	-0.48 (-14.28)	-0.39 (-11.92)	-0.60 (-15.73)	-0.81 (-16.72)	-0.82 (-16.57)
Travelcosts_car	-0.20 (-3.70)	-0.19 (-4.43)	-0.45 (-6.13)	-0.49 (-5.88)	-0.49 (-5.76)
Activity_CHO	-0.13 (-2.34)	-0.053 (-1.16)*	-0.21 (-3.30)	-0.26 (-3.37)	-0.28 (-3.68)
Travel_company_CH	-0.21 (-5.78)	-0.21 (-6.83)	-0.13 (-3.46)	-0.22 (-4.70)	-0.21 (-4.53)
Travel_company_car	-0.19 (-2.93)	-0.15 (-2.78)	-0.30 (-3.58)	-0.28 (-3.01)	-0.30 (-3.19)
Walkingtime_car	0.055 (1.50)*	0.029 (0.99)*	0.11 (2.34)	0.083 (1.63)*	0.089 (1.72)*
AbleToWork_car	0.23 (4.22)	0.17 (4.04)	0.47 (1.96)*	0.42 (2.25)	0.41 (1.89)*
WillingToWork_car	0.57 (10.66)	0.44 (9.29)	1.10 (4.44)	0.80 (4.33)	1.01 (4.44)
CarOwnership_car	-0.43 (-3.26)	-0.34 (-3.53)	-0.76 (-1.29)*	-0.75 (-1.92)	-0.81 (-1.46)*
Age2_car	-0.27 (-2.65)	-0.22 (-2.96)	-0.44 (-0.96)*	-0.34 (-0.93)*	-0.40 (-0.75)*
Gender_car	0.20 (3.91)	0.14 (3.69)	0.35 (1.59)*	0.34 (1.97)	0.35 (1.68)*
Convenience_car	-0.78 (-12.87)	-0.55 (-8.71)	-1.60 (-5.85)	-1.27 (-5.53)	-1.81 (-5.00)
Safety_car	-0.35 (-6.46)	-0.25 (-5.75)	-0.65 (-2.68)	-0.59 (-3.12)	-0.71 (-2.38)
DO_other_car	0.25 (3.00)	0.21 (3.28)	0.53 (1.38)*	0.17 (0.58)*	0.21 (0.51)*
Mode_BMT_car	-0.66 (-3.26)	-0.58 (-3.83)	-1.13 (-1.30)*	-0.61 (-0.94)*	-0.35 (-0.31)*
Mode_other_car	0.95 (4.21)	0.85 (4.83)	1.46 (1.57)*	1.16 (1.69)*	0.92 (0.73)*
Adj. Rho-Square	0.289	0.292	0.411	0.455	0.458

** = not significant in a 95% confidence interval, CHO = chauffeur-driven office car, CHL = chauffeur-drive leisure car.*

Travel time In general, an increase in travel time (unit: utile/min) is most negatively valued in the chauffeur-driven leisure car.

Travel costs However, an increase of one euro in travel costs (unit: utile/€) is according the model results least negatively experienced by the chauffeur-driven leisure car travellers, while the office-car users experience most disutility by an increase in travel expenses.

Travel company & activity Just as in the AV-case, saving time at the office is preferred over working extra time, and travelling alone is preferred over travelling with companions. However, the NL model indicated an insignificant parameter for *Activity_CHO*.

Walking time The walking time parameter is only significant in the error-component model. It has a positive value (0.11), which means that an increase in walking time adds utility for the car alternative. There are situations thinkable where this is true (e.g. 25 degrees and sunshine), however it is very uncommon outcome.

Socio-economic factors If respondents are not able to work in a car and not willing to work in an AV a preference has been observed for the conventional car. Three models indicate that, seen the negative value, if one does not own a car he or she prefers the chauffeur-driven car.

The MNL results indicate that people in the age category 26-60 do not prefer the conventional car, while respondents younger than 26 years do prefer the normal car.

The significant positive values for the gender parameter in the MNL, NL and taste-ML model indicate that males prefer driving a car themselves while females prefer chauffeur-driven cars. Furthermore, the MNL model indicates that bus/tram/metro (*Mode_BMT_car*) users prefer the chauffeur-driven cars, while the people who do not use either train, car, BMT, bike or car-pool have a preference for the conventional car. Current car users have, surprisingly, a preference for a chauffeur-driven car (-0.66 * -1 + 0.95 * -1 = -0.29 for car). People in the occupation category 'other', e.g. jobless people, prefer the conventional car, while full-time workers prefer the chauffeur-driven car the most.

Attitudinal factors Ultimately, the importance of attitudinal factors is shown by these models. It is indicated that a positive attitude towards the conveniences of automated driving and the safety aspects of automated driving result in a preference for a chauffeur-driven car.

VOTT Table 7.16 shows the mean VOTT estimates and the standard deviations. In all but one model the mean VOTT estimate of the chauffeur-driven office car traveller is the lowest. Only the taste-ML model indicates that car users have a lower mean VOTT. The standard deviations of the VOTT distributions of car travellers are very high, which means that these distributions have a large spread. Furthermore it is striking that the mean VOTT of CH-leisure users is lower than the VOTT of conventional car travellers using the MNL model and the NL model, but higher using the ML models.

Table 7.16: Mean VOTT estimates and standard deviations chauffeur-case in [€/hour] (full sample).

	MNL	*NL*	*Error-component ML*	*Taste ML*	*Combined ML*
Mean VOTT car	8.81	6.69	8.06	4.95	6.63
Sigma VOTT car	-	-	-	13.06	10.20
Mean VOTT CHO	3.66	3.16	4.00	5.67	5.61
Sigma VOTT CHO	-	-	-	4.26	4.21
Mean VOTT CHL	5.91	5.48	8.72	9.06	8.86
Sigma VOTT CHL	-	-	-	4.70	4.55

The Delta method was applied to determine whether the ratios in the first three models are significant. The result (Table 7.17) is that all estimates are significantly different from zero. After applying Welch's t-test it appeared that the mean VOTT of the conventional car users and the CH-leisure users do not differ significantly from each other in all three models. The mean VOTT of office-car users and leisure-car users do not differ significantly in the MNL model as well (see Table 7.17).

Table 7.17: Delta method and Welch's t-test results VOTT ratios CH-case (full sample).

	MNL	*NL*	*Error-component ML*
Delta-method results			
Mean VOTT car	4.55	4.90	7.70
Mean VOTT CHO	4.72	4.19	5.98
Mean VOTT CHL	6.45	6.00	8.24
Welch's t-test			
VOTT car – VOTT CHO	2.46	2.26	2.99
VOTT car – VOTT CHL	1.35*	0.74*	0.26*
VOTT CHO – VOTT CHL	1.87*	1.96	3.05

** = not significant in a 95% confidence interval.*

The results indicated that a big part of the probability density of the car-specific travel time parameter has a positive value. The probability of having a positive travel time parameter for the AV-office and the AV-office is significantly lower.

High probabilities of estimating a positive time parameter for the normal car were found. This is not odd given the large standard deviation of the distributions. So, a large variety exists among the VOTT for the different traveller groups. Because only the ratio of the mean time parameter with the fixed costs parameter does not provide all information, the 95% confidence intervals are calculated and shown in Table 7.18. This table indicates that ignoring the spread of the VOTT leads to a loss in information.

Table 7.18: 95% quantile intervals for the distribution of the VOTTs in [€/hour] (full sample).

	Taste ML Lower 95% quantile limit	*Taste ML Upper 95% quantile limit*	*Combined ML Lower 95% quantile limit*	*Combined ML Upper 95% quantile limit*
β_{TT_CAR}	-20.64	30.55	-13.37	26.63
$\beta_{TT\_CH\text{-}OFFICE}$	-2.68	14.03	-2.63	13.86
$\beta_{TT\_CH\text{-}LEISURE}$	-0.16	18.28	-0.05	17.78

7.5.2 RESULTS SAMPLE EXCLUDING NON-TRADERS (CHAUFFEUR-CASE)

Ultimately, the results of the models estimated using data with the exclusion of non-traders are described. The same models are estimated as with the previous data. The same assumptions and procedures for the modelling was applied. Table 7.19 shows the model fit of the estimated models.

Table 7.19: Model fit chauffeur-case (excl. non-traders) models.

Model	*# of parameters*	*Adj. Rho-Square*	*Final LL*	*LRS*
Null	0	-	-1924.769	-
MNL base	11	0.168	-1591.194	667.149
MNL extended	15	0.182	-1559.707	730.123
NL	-	-	-	-
ML error-component	16	0.196	-1532.086	785.366
ML taste	18	0.219	-1486.101	877.335
ML combined	-	-	-	-

The following equations of the LRS show that each significantly estimated model fits the data better than the previous model. Given the adjusted Rho-Square and the LRS, it is determined that the taste-ML model fits the data best.

Equation 38

$$\mathrm{LRS} = -2 * (\mathrm{LL}_{\mathrm{MNL\ base}} - \mathrm{LL}_{\mathrm{MNL\ ext.}}) = -2 * (-1591.194 - -1559.707) = 62.97$$

Equation 39

$$\text{LRS} = -2 * (\text{LL}_{\text{MNL ext.}} - \text{LL}_{\text{ML error-comp.}}) = -2 * (-1559.707 - -1532.086) = 55.24$$

Equation 40

$$\text{LRS} = -2 * (\text{LL}_{\text{ML error-comp}} - \text{LL}_{\text{ML taste}}) = -2 * (-1532.086 - -1486.101) = 91.97$$

Table 7.20 shows the estimated parameter values of all models.

Table 7.20: Estimation results of the chauffeur-case models (excl. non-traders).

Parameter	*MNL*	*NL*	*Error-component ML*	*Taste ML*	*Combined ML*
Constant_car	0.00	0.00	0.00	0.00	0.00
Constant_CH	1.51 (2.13)	1.51 (2.13)	1.39 (1.83)*	2.64 (3.19)	2.57 (3.11)
σ_constant_CH	-	-	0.80 (8.41)	-	0.156 (0.69)*
Nest_parameter	-	1.00 (0.48)*	-	-	-
Traveltime_CHL	-0.066 (-9.82)	-0.066 (-9.82)	-0.072 (-10.29)	-0.089 (-10.45)	-0.088 (-10.41)
Traveltime_CHO	-0.044 (-6.36)	-0.044 (-6.36)	-0.047 (-6.59)	-0.066 (-7.64)	-0.066 (-7.61)
Traveltime_car	-0.052 (-8.10)	-0.052 (-8.10)	-0.059 (-8.55)	-0.061 (-7.84)	-0.061 (-7.88)
σ_traveltime_CHL	-	-	-	0.030 (7.02)	0.031 (6.80)
σ_traveltime_CHO	-	-	-	0.032 (7.11)	0.031 (7.21)
σ_traveltime_car	-	-	-	0.030 (6.85)	0.029 (6.41)
Travelcosts_CHL	-0.54 (-12.83)	-0.54 (-12.83)	-0.55 (-12.87)	-0.67 (-13.58)	-0.67 (-13.57)
Travelcosts_CHO	-0.63 (-16.19)	-0.63 (-16.19)	-0.66 (-16.41)	-0.76 (-16.62)	-0.76 (-16.61)
Travelcosts_car	-0.38 (-5.12)	-0.38 (-5.12)	-0.43 (-5.59)	-0.40 (-5.00)	-0.40 (-5.02)
Activity_CHO	-0.19 (-2.78)	-0.19 (-2.78)	-0.21 (-3.04)	-0.25 (-3.27)	-0.25 (-3.25)
Travel_company_CH	-0.20 (-4.72)	-0.20 (-4.72)	-0.18 (-4.26)	-0.22 (-4.71)	-0.22 (-4.72)
Travel_company_car	-0.26 (-3.15)	-0.26 (-3.15)	-0.29 (-3.34)	-0.25 (-2.80)	-0.25 (-2.80)
Walkingtime_car	0.045 (1.02)*	0.045 (1.02)*	0.061 (1.31)*	0.056 (1.14)*	0.055 (1.11)*
WillingToWork_car	0.27 (4.44)	0.27 (4.44)	0.31 (3.12)	0.32 (2.83)	0.35 (3.02)
CarOwnership_car	-0.29 (-1.93)	-0.29 (-1.93)	-0.34 (-1.43)*	-0.49 (-1.76)*	-0.45 (-1.65)*
Convenience_car	-0.30 (-3.59)	-0.30 (-3.59)	-0.34 (-2.50)	-0.40 (-2.63)	-0.39 (-2.50)
Safety_car	-0.19 (-2.80)	-0.19 (-2.80)	-0.21 (-1.97)	-0.23 (-1.88)*	-0.21 (-1.76)*
Adj. Rho-Square	0.182	0.181	0.196	0.219	0.218

** = not significant in a 95% confidence interval, CHO = chauffeur-driven office car, CHL = chauffeur-drive leisure car.*

Nest parameter As can be seen in the table none of the nest parameters is significant, which means that normal MNL models were estimated.

Standard deviations In the combined ML model the standard deviation of the ASC for chauffeur-driven cars is not significant. This means that a taste ML is estimated, since the sigma-values of the travel time parameters are significant. Significant standard deviations for the travel time distributions indicate that heterogeneity exists for individuals in travel time. Furthermore, in the MNL model an unobserved preference for a chauffeur-driven car compared to the conventional car is observed.

Travel time In all models an increase in travel time (unit: utile/min) is on average valued most negatively when travelling in the leisure-car compared to the other alternatives.

Travel costs An increase in travel costs (unit: utile/€) is experienced worst when travelling in the chauffeur-driven office car, while an increase in travel costs is valued least negatively in the car alternative.

Travel company & activity Also these models indicate that travelling alone is preferred over travelling with family/friends, and saving time at the office is preferred in comparison to working additional time.

Walking time The walking time coefficient is in none of the models significant, and therefore equals 0.00.

Socio-economic variables Regarding car ownership and willing to work in an AV, the same behaviour is observed as in the models estimated using the full sample.

Attitudinal factors In these models the same attitudinal latent factors as estimated in the full sample models are found significant. The attitudinal factor estimates are in line with the results of the full sample.

VOTT Table 7.21 provides the mean VOTT estimates per model per traveller group. In all cases the mean VOTT of the chauffeur-driven office car travellers is lower than the VOTT estimates of car travellers and leisure-car travellers. The mean VOTT of car travellers is in every model the highest with respect to the other mode users.

Table 7.21: Mean VOTT estimates and standard deviations chauffeur-case in [€/hour] (excl. non-traders).

	MNL	*NL*	*Error-component ML*	*Taste ML*	*Combined ML*
Mean VOTT car	8.31	8.31	8.21	9.10	9.10
Sigma VOTT car	-	-	-	4.48	4.48
Mean VOTT CHO	4.22	4.22	4.28	5.22	5.22
Sigma VOTT CHO	-	-	-	2.48	2.48
Mean VOTT CHL	6.23	6.23	7.82	7.96	7.96
Sigma VOTT CHL	-	-	-	2.73	2.73

After applying the Delta method, it became clear that all VOTT estimates estimated with the MNL model and the error-component model are significantly different from zero. To compare these ratios with each other the adapted version of Welch's t-test was used. This t-test indicated that the VOTT of car users and leisure-car users do not differ significantly from each other in both models. The other ratios do differ significantly from one another. The results of the Delta application and the Welch's t-test are shown in Table 7.22.

Table 7.22: Delta method and Welch's t-test results VOTT ratios CH-case (excl. non-traders).

	MNL	*NL*	*Error-component ML*
Delta-method results			
Mean VOTT car	6.61	6.61	7.28
Mean VOTT CHO	5.98	5.98	6.28
Mean VOTT CHL	6.78	6.78	8.28
Welch's t-test			
VOTT car – VOTT CHO	2.84	2.84	3.26
VOTT car – VOTT CHL	0.68*	0.68*	0.44*
VOTT CHO – VOTT CHL	2.63	2.63	3.77

** = not significant in a 95% confidence interval.*

This method is, due to the nature of the normal distribution of the mode-specific travel time parameters, not applicable for the VOTT distributions found with the taste ML model. The results indicated that only a small probability exists of estimating positive travel time values for the conventional car, CH-office and CH-leisure users.

At last, a calculation of the variance for the ratio of coefficients has been done. The results are shown in Table 7.23. This table shows that within the 95% confidence interval only positive VOTT values are estimated.

Table 7.23: 95% quantile intervals for the distribution of the VOTTs in [€/hour] (excl. non-traders).

	Taste ML *Lower 95% quantile limit*	*Taste ML* *Upper 95% quantile limit*
β_{TT_CAR}	0.31	17.88
$\beta_{TT\_CH\text{-}OFFICE}$	0.35	10.09
$\beta_{TT\_CH\text{-}LEISURE}$	2.61	13.30

7.6 DISCUSSION

This subsection contains a reflection on the results. The first part contains the discussion of the results. It is discussed whether the results are according expectation and possible explanations are sought for unexpected behaviour. The second part reflects on the used models.

7.6.1 DISCUSSION OF THE RESULTS

Latent factors Bansal et al. (2016) already found that the safety aspect of automated driving is an important incentive to upgrade a conventional car with AV possibilities. The results of this study show that safety is again an important factor regarding automated driving. This study confirmed that the safety aspects of automated driving could people tempt to choose for an AV. Furthermore, the found latent factors are in line with the latent factors found by Yap et al. (2016).

NL model results It was expected that the AV with office interior and the AV with leisure interior belonged to the same nest. This expectation was based on the fact that both AV alternatives share the self-driving car principle. Secondly, it was expected that the chauffeur-driven office car and leisure car belong to the same nest. However, the results indicated that this nest does not exist. A possible explanation is that respondents experience working and leisure time completely different.

However, two NL models indicated significant nest parameters. A nest has found where the AV-office and the conventional car, and the CH-office and the conventional car belong to the same nest. This result was not according expectation, and has only been found when using the complete datasets. This implies that including non-traders leads to nests, which are not identified by the NL models estimated using only the traders.

Parameter values ML models All mean VOTT estimates determined by the ML models are higher than the VOTT estimates determined by the MNL models. This is also observed for (almost) every estimated parameter, regardless of the dataset. Hess et al. (2004) observed higher mean travel time parameters and VOTT estimates with the ML models compared to the MNL model. The phenomenon that the costs parameters were also higher was not observed by Hess et al. (2004).

Combined ML model results The combined ML models estimated using the datasets excluding non-traders did not fit the data better than the taste ML model. Since both the error-component ML model and the taste ML model estimate significant standard deviations, it was expected that combining these models would estimate four significant standard deviations. However, only the standard deviations of the time parameters were significant. This result means that the heterogeneity that was found in the travel time parameters explains better the data than the heterogeneity in the unobserved preference.

Heterogeneity measurements Furthermore, it is observed that less heterogeneity in the travel time parameters was measured using data that excludes non-traders compared to using the full sample. This was observed in both the AV-case and the chauffeur-case. Leaving out non-traders reduces the level of heterogeneity in the travel time parameters.

Positive walking time parameter While most of the models estimated the walking time parameter for the car alternative insignificant, some models did estimate this parameter significant. In the case the walking time was estimated significantly it was valued positively. This means that an increase in walking time by one minute is experienced positively, and thus adds utility to the car alternative. There are situation where this situation is correct. For example, if one has to choose between walking 5 minutes from place A to place B along a busy road or walking 20 minutes through a quiet nice park. However in studies such as Arentze & Molin (2013), Axhausen & Polak (1991), Wardman (2001) and Yap et al. (2016) it is explained that a walking time coefficient must have a negative value. So, it is concluded that a positive walking time parameter is an odd outcome.

Preference of retirees and ≥60 year old people The MNL model and the error-component model estimated using the AV-case data that excludes non-traders indicated that people in the age category 60 years and older prefer the conventional car, while retirees have a preference for an AV. This is, at first glance, odd. However, in chapter 6 we concluded that mainly respondents who are older, low educated, retired and/or 'other' employed showed non-trading behaviour. Almost all non-traders opted consequently the conventional car. Leaving out 45.0% of the retirees and 40.8% resulted in this odd outcome.

VOTT AV users All models using the data excluding non-traders showed consistent and stable mean VOTT estimates. AV-office users have always the lowest mean VOTT (€4.93-6.26 per hour), AV-leisure users have always the highest VOTT (€10.47-11.24 per hour), and car users have always a VOTT in between the other two values (€7.83-8.37 per hour). The mean VOTTs estimated using the full sample were unstable and inconsistent in ranking. It is concluded that the models using the trader-data provide better mean VOTTs, and are therefore used to answer the research questions.

The high mean VOTT of AV-leisure travellers was unexpected, since the expectation was that a trip in an AV should have a better experience compared to a trip in a conventional car. An explanation of the high VOTT of AV-leisure users could be that only being productive would generate a lower VOTT and that people do not prefer to have leisure time in a car. Because one cannot work in the AV-leisure car, it cannot leave the office later to substitute travel time for time at home, so this benefit does not count for the AV-leisure users.

A second explanation for this result is that respondents cannot imagine what one can do in an AV. Because people are already working while being in a vehicle (e.g. train travelling), people could easier understand what it includes to work in an AV-office. Activities such as playing with your children and gaming are currently not common activities in a vehicle. So, it could be that respondents cannot foresee how these types of activities develop in an AV-leisure.

A third explanation is that it is not well enough explained what benefits an AV-leisure has in the morning. It is for example possible to have breakfast in the AV-leisure such that less time is needed in the morning. This has the result that one could stay longer in his or her bed. Another example is that one is able to change clothes or put up some make-up in the AV-leisure . However, the reason for this results is unclear, so it is important to do further research to the VOTT of AV-leisure users.

VOTT CH users The mean VOTT estimates of the full sample models were unstable and inconsistent, while the mean VOTTs computed from the models using the traders only showed stable VOTTs and produced a consistent ranking. Regarding the trader-models, the mean VOTT of the CH-office travellers was always lowest (€4.22-5.22 per hour), compared to VOTT of the CH-leisure users (always middle value; €6.23-7.96 per hour), and the VOTT of the conventional car user (always highest; €8.21-9.10 per hour). The full-sample show all different results. The mean VOTT of the CH-office user (€3.66-5.67 per hour) is lowest in all models except the taste ML model. The mean VOTT of the car traveller (€4.95-8.81 per hour) is very unstable. The mean VOTT of the leisure-car traveller (€5.91-9.06 per hour) is one time the middle value, and further the highest value. Next to a strong fluctuating VOTT, the VOTT of conventional car users has a very large standard deviation according the full-sample models.

VOTT car users At last the found mean VOTT estimates for car users are reflected. Kouwenhoven et al. (2014) found an average VOTT of €9.00 per hour using mean-dispersion MNL models and a latent class model. Yap et al. (2016) estimated the VOTT of car travellers at €9.30-9.90 per hour making use of a combined MNL and latent variable model. Arentze & Molin (2013) estimated two VOTTs for car drivers making use of an error-component ML model. The VOTT is €12.42 per hour for short trips, while the VOTT is €22.74 for long trips. The mean car-user VOTT found with both AV-case sample varies between €7.83-8.77 per hour and is in line with Kouwenhoven et al. (2014) and Yap et al. (2016), but are considerably lower than the VOTTs of Arentze & Molin (2013).

Regarding the chauffeur-case, the models estimated using the full sample indicate car mean VOTTs around €4.95-8.81 per hour. Two low values (€4.95 per hour and €6.93 per hour) are found in respectively the taste ML model and the combined ML model. The mean VOTT estimates of the error-component model and the MNL model are in line with Kouwenhoven et al. (2014) and Yap et al. (2016). All mean VOTTs indicated from the trader-sample are around €8.21-9.10. These values are almost similar to Kouwenhoven et al. (2014) and Yap et al. (2016).

It is striking that the VOTTs indicated by the error-component ML models from this study are not in line with the error-component ML model results of Arentze & Molin (2013). Several reasons are identified. First, different attribute levels for (main) travel time, travel costs and walking time are used. Second, the sample size of Arentze & Molin (2013) is much larger than the sample size of this study. Thirdly, this study is executed in 2016/2017, whereas Arentze & Molin (2013) used data from 2011 and 2012. At last, their study focusses on the car, bike, BMT, local train and intercity train, while the focus of this study is on measuring the trip experience of AV travellers compared to car travellers. Arentze & Molin (2013) use a normal distribution in their error-component ML model too.

The MNL models have the same structure as the model used by Yap et al. (2016). No mean-dispersion MNL models and latent class models are used in this study, which were applied by Kouwenhoven et al. (2014).

7.6.2 REFLECTION ON THE MODELS

Model fitness Three different types of discrete choice models are used in this study. An important parameter to determine which model suits the data best is the adjusted Rho-Square. When the adjusted Rho-square is above 0.1 it is considered as an acceptable model fit. To determine which model fits the data best, the likelihood ratio test (LRS) is used as well. This test indicated that for the combined-ML model fits the full-sample data best, while the taste-ML model fits the data excluding non-traders best.

Model use Estimating ML models are very useful when, for example, forecasting market share for a tolled road, because it shows the variety in one's willingness to pay and thus the effectiveness of the measure (Hensher & Goodwin, 2004). However, estimating a ML model is time consuming. The ML model makes use of a distribution, which is chosen by the analyst. So, it is possible that the researcher uses a normal distribution, while a triangular distribution represents the data better. Thereby, it is useful to question whether researching the distribution of the VOTT is useful for policymakers.

In my opinion the answer is context dependent. In the case a problem requires a quick answer, it is recommended to use a NL model. The NL model applications are known by transportation policymakers and this method allows quick results. NL models provide a good indication of the importance of the given variables, and prevents overestimation by allowing correlation between alternatives. The ML application is able to capture these effects as well and it allows randomness in the unobserved preference and taste parameters, and it copes with panel effects.

So, if a thorough research is required to solve certain problems or to answer certain research questions, it is recommended to apply ML models. A ML model provides insights in heterogeneity in the unobserved preference and in the taste. It results not in a homogenous parameter value, but in a range of values. These values follow a distribution with an estimated mean and standard deviation. An additional benefit of ML models is that panel effects are allowed. The MNL and NL model assumes that every choice made by the same individual is not correlated, while choices by the same individuals are generally correlated. This leads to overestimated t-values, thus in significant parameters, while in face they are not (Chorus, 2016).

It can be concluded that the model choice depends heavily on the nature of the problem. For quick and dirty results the use of NL models is acceptable. However, more elaborated models should be used for obtaining more reliable results.

Full sample vs. sample excl. non-traders In this study all models were estimated with the full sample and with the sample excluding non-traders. Hess et al. (2010) concluded that pre-analysis procedures to find non-trading behaviour could influence the model estimation significantly. The exclusion of non-trading led to more stable model estimations in both the AV-case and chauffeur-case. It is therefore recommended for further research to make a distinction between traders and non-traders as well.

All the topics of discussion are summarised in Table 7.24.

Table 7.24: Summary of the discussion of results and models.

	Expectation	*Result*
Latent factors		In line with literature (Bansal et al. (2016) and Yap et al. (2016): Positive attitude towards safety aspect of AV result in preference for AV Positive attitude towards conveniences of AV results in preference for AV Not trusting AVs results in preference for conventional car
NL model results	AV/CH-office and AV/CH-leisure belong to same nest	AV/CH-office and conventional car in same nest. Results only found significant when estimating with the full sample
Parameter values ML models	Higher than parameter values of MNL and NL models	Higher than parameter values of MNL and NL models
Combined-ML results	Significant, if error-component ML and taste-ML model are significant	Expectation is only correct when estimating with full sample.
Heterogeneity traders vs. non-traders	Less heterogeneity if non-traders are excluded	Less heterogeneity if non-traders are excluded
Walking time	Negative effect on preference for conventional car	Insignificant or positive effect on preference for conventional car
Preference retirees and ≥60 year old people	Same preference	Retirees prefer AVs and ≥60 year old prefer conventional car according dataset excluding non-traders. However, many retirees and ≥60 year old people are excluded due to non-trading behaviour. They mainly opted always the conventional car.
VOTT AV users	VOTT of AV-office users and AV-leisure users is lower than VOTT of conventional car users	VOTT of AV-office users is lower than the VOTT of conventional car users VOTT of AV-leisure users is higher than the VOTT of conventional car users
VOTT CH users	VOTT of CH-office users and CH-leisure users is lower than VOTT of conventional car users	VOTT of CH-office users and CH-leisure users is lower than VOTT of conventional car users
VOTT car users		In line with Kouwenhoven et al. (2014) and Yap et al. (2016). Not in line with Arentze & Molin (2013)
Model fitness		Full-sample models: combined-ML model fits data best Sample excl. non-traders: taste-ML model fits data best
Model use		For quick and dirty results: NL models For more reliable results: ML models
Full sample vs. sample excl. non-traders		Samples excluding non-traders provides more consistent and stable outcomes

This chapter contained three main parts. In the first part the results of the latent variable models were given. It came forward that three attitudinal factors were identified, which could influence the decision-making regarding AVs. These factors are (dis)trust in automated driving, conveniences of automated driving and safety of automated driving. The second part included the results of the estimated discrete choice models. It became clear that the VOTT of the AV-office users is lower than the VOTT of the conventional car users, while the VOTT of the AV-leisure users is higher than the VOTT of the conventional car users. At last, all results were discussed in paragraph 7.6. The results of this study were compared to results of other relevant studies, and explanations were given for the unexpected results.

8 IMPLICATIONS, CONCLUSIONS AND RECOMMENDATIONS

The aim of this study was to explore how people in the Netherlands experience a trip in a full-automated vehicle compared to a trip in a conventional car by exploring how VOTT of AV users will develop in comparison to the car traveller's VOTT. Because full-automated vehicles are currently non-existing modes of transport, a SP experiment has been conducted. In chapter 7 the results of the latent variable models and the discrete choice models were described and discussed. This chapter builds on the previous chapters by drawing conclusions from the results, exploring implications of the results and by formulating recommendations.

The remainder of this chapter is divided as follows. First implications are formulated. Then, the remaining sub research questions are answered. Subsequently, an answer on the main research question is given and the last conclusions are drawn. After the conclusions, recommendations for further research are proposed. The chapter ends with a personal reflection on the research (process).

8.1 IMPLICATIONS

In the chapter 1 and 2 it was mentioned that the value of travel time savings is of big importance in cost-benefit analysis (CBA) for infrastructure related projects. The value of travel time savings accounts for approximately 60 to 80 per cent of the monetised benefits of new infrastructure (Mackie et al., 2001). An adaptation in VOTT could therefore cause big changes in the benefits. This section tries to deepen on how the results have impact on the current CBA in the Netherlands and it explores the effect of AVs on other modes of transport.

A CBA is a mandatory analysis for all large infrastructural projects in the Netherlands and aims to monetise all direct, indirect and external effects of an infrastructure project (Centraal Planbureau, 2013). A CBA compares the effects of a project with the status quo; the reference scenario. The reference scenario is the current situation, such that the effects of a new project are comparable in monetising units with the situation where no action will be undertaken (Mouter, 2013). The value of travel time savings is one of the most crucial concepts in transport CBAs, since it accounts for approximately 60 to 80 per cent of the monetised benefits of new infrastructure (Mackie et al., 2001). In this case, a social VOTT is used for monetising travel time accruing from a transport project (Kouwenhoven et al., 2014).

Mouter (2015) discusses the current practice of the use of VOTT in Dutch CBAs. He mentions that in the Netherlands the VOTT for non-business trips is differentiated across journey purpose (commuting and other) and modes. Also a differentiation is made between income groups, however this is only used in assessing the effects of road pricing policies, and not in CBAs. The VOTT is not differentiated across regions, since the Netherlands is too small to make such differentiation compared to for example Germany and the United Kingdom. Besides, it is politically too sensitive to differentiate between the metropolitan area (Randstad) and the rural areas.

This study focussed on exploring the VOTT of AV users in the Netherlands during the morning peak. It is found that the VOTT for travellers with an AV in which they can work is around €5.39 per hour, which is 33.0% lower compared to conventional car traveller's VOTT (paragraph 8.2). However, people who travel with an AV in which they have leisure time are willing to pay more money to reduce their travel time compared to car travellers (€10.84; +34.9%). Since 60 to 80 per cent of the monetised befits are dependent on travel time savings, an increase or decrease of the VOTT could have big impacts in transport project appraisals. A project could not be appropriate anymore or another alternative appears to be more feasible than the chosen alternative.

A lower VOTT for AV-office users indicates that it is potentially an attractive way of transport such that the travel demand increases. A higher travel demand leads to a higher trip generation, which could lead to higher monetised benefits. However, more trips mean extra traffic, which leads to more congestion. Puylaert (2016) already concluded that the introduction of level 1, 2 and 3 AVs results in more traffic and more congestion. Nonetheless, the precise effect of a lower VOTT for AV-office users compared to conventional car users on travel demand is not known and considered to be a topic for further research.

AVs have the ability to influence the road capacity as well. AVs are capable of forming platoons. In a platoon, AVs from a long row of vehicles that drive closely behind each other. Automated driving applications such as adaptive cruise control improve the traffic-flow stability and efficiency, and therefore improve the road capacity (Arnaout & Bowling, 2011; Hoogendoorn, van Arem, & Hoogendoorn, 2014; Schakel, van Arem, & Netten, 2010; Tampère, Hoogendoorn, & Van Arem, 2009; Van Arem, Van Driel, & Visser, 2006). A higher road capacity relates to less congestion when other factors are kept constant. Again, the effect of a lower VOTT for AV-office users compared to conventional vehicle users on road capacity is a topic for further research.

The presence of automated vehicles on the motorways could also lead to changes in the environmental aspect. As mentioned in the introduction AVs could lead to a higher demand of mobility, which means more vehicles on the road. With the current fuel consumption of cars, more vehicles lead to more congestion and emissions. This has a negative impact on the environment, thus higher environmental costs in CBAs. Further research must be done to determine the environmental costs of AVs.

On the other hand, with only full-automated vehicles on the road, the traffic safety should increase. Since most accidents are caused by human error (NHTSA, 2008), the use of AVs should eliminate these types of accidents . It is not indicated that when only AVs drive around that the traffic would be perfectly safe, but theory mentions that the safety should improve (Fagnant & Kockelman, 2015). This means that the safety benefits will be more positive, however further research is necessary to determine monetised benefits of AVs on traffic safety.

The lower VOTT for AV-office users signifies that the disutility of travel decreases. This causes the effect that people could travel further, since travelling is less a burden. In the last 2 decades of the 20th century, the average travel time per day per person in the Netherlands (travel time budget: TTB) increased from about 58 minutes to approximately 72 minutes (van Wee, Rietveld, & Meurs, 2006). However, during the economic crisis the TTB decreased to 61.8 minutes (CBS Statline, 2016g). The concept of (a constant) TTB has been researched, see e.g. (Golob, Beckmann, & Zahavi, 1981; Hupkes, 1982; Mokhtarian & Chen, 2004; Roth & Zahavi, 1981). Van Wee et al. (2006) gave explanations why the TTB increased over time in the Netherlands. One of their explanations was that increased possibilities for combining travel with other activities had been measured. This combination reduces the disutility of travel time. It is therefore likely that travel times will increase rather than the number of trips (van Wee et al., 2006). So, the introduction of the AV, which facilitates the combination of travel and other activities, could lead to an even higher TTB in the Netherlands. Considering that the average travel speed remains the same, it would result in more distance travelled in the Netherlands. How the relationship between full-automated driving and TTB will develop is a topic for further research.

Furthermore, it is proved that commuters as well as business travellers use travel time in public transport as working time and relaxing time (Fickling et al., 2009; Kroes & Koopmans, 2014). Due to a high level of comfort, this group is able to conduct working activities (Warffemius et al., 2016). This is the case for automated vehicles as well. Warffemius et al. (2016) claims that this high comfort adds utility, which is not taken into account in current CBAs. So in this paper, Warffemius et al. (2016) describe a new method to compute key numbers to express comfort differences in monetised units. By having a comfort multiplier and the VOTT parameter, social benefits are higher than in the initial situation. However, Annema (2017) has big doubts whether this method is justified and does not recommend to use this method.

So, based on travel time and the VOTT, this study indicates that the monetised benefits of new infrastructure could drop compared to the current situation. This raises the question whether investing in new infrastructure is necessary, since longer travel times are more acceptable due to the ability of doing work. Although, it is not tested if the VOTT of AV-travellers remains the same when they are in the middle of congestion. When only the travel time savings are taken into account, investments in new roads could be reconsidered. Nonetheless, new infrastructure aims not only to improve the travel time, but the travel time reliability as well (Kouwenhoven et al., 2014). To monetise an improvement in predictability of travel time, the value of travel time reliability (VOR) is invented (Carrion & Levinson, 2012). Since the duration of a journey in an AV is of lesser concern, the reliability of a journey could become more important. As mentioned before, AVs could lead to more traffic, and thus longer journey times. More traffic on the roads result in less travel time reliability. Thus, it is thinkable that if one leaves home to work on Monday at 8:00 AM he or she arrives at 9:00 AM at work, while at 10:00 AM on Tuesday, at 9:15 AM on Wednesday and so on. However, the concept of travel time reliability was not in the scope of this research and is a topic for further research.

The a low VOTT for AV users could also have an impact on the use of public transport. Travelling by AV-office could be a good substitute for travelling by train, since the train is a commuting mode in which travellers could currently execute working activities too (Fickling et al., 2009; Kroes & Koopmans, 2014). The VOTT of train travellers is estimated on €9.25 per hour (Kouwenhoven et al., 2014). This VOTT is significantly higher than the VOTT found for AV with office interior travellers. A substitution of train travellers by AV travellers has several consequences. Firstly, the intensity of the road traffic increases, because more trips are generated. This results in more congestion and more emissions. Secondly, the demand for travelling by train is going down. This could imply that investments in rail as a whole become less feasible and that rail operations will be less profitable.

The introduction of full-automated vehicles has an effect on the bike using, BMT using and car-pooling as well, since AVs could be a substitute for these modes of transport. It is imaginable that this has big consequences. More road using, more health issues, and so on. It is important to know the impact of AV usage in relation to other modes of transport.

A summary of all relationships between the VOTT of automated driving and CBA variables are shown in Figure 8.1. A green arrow means that an increase in one factor leads to an increase in the related factor. A red arrow indicates that a decrease in one factor leads to a decrease in the related factor. A double-headed arrow means that the relation is bilateral. An example, an increase in the attractiveness of the conventional car leads to an increase in the road travel demand.

For synthesis, it became clear that the VOTT of AV users could impact the current CBA methodology. It is must be researched how the VOTT's of AV travellers relate to the road capacity, travel demand, travel time savings, travel time reliability, environmental effects and safety effects. Furthermore, it came forward that AVs could become a substitute for current modes of transport. In what extent the introduction of AVs will change the model split is a topic for further research as well.

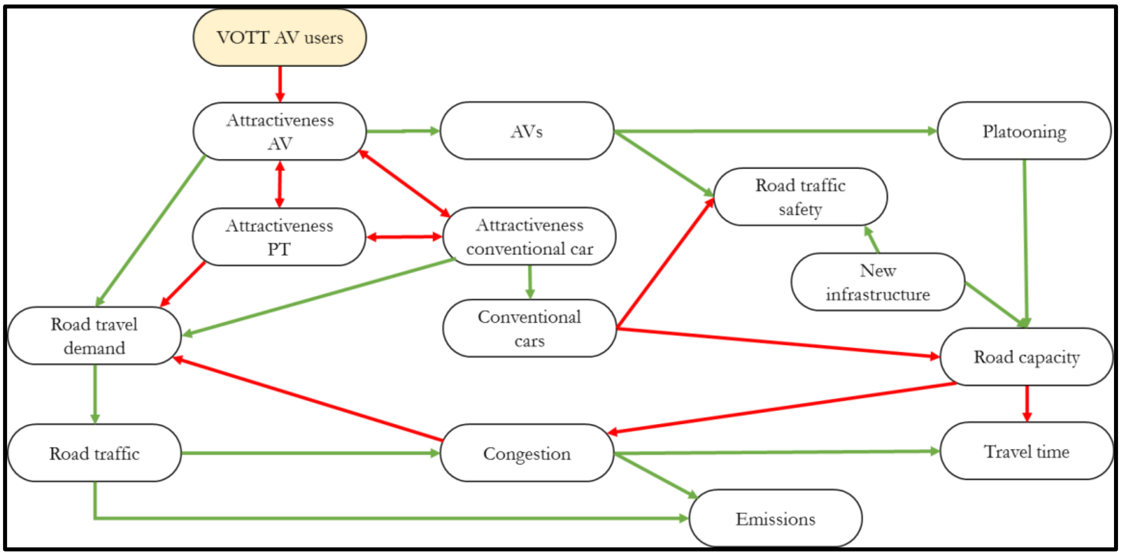

Figure 8.1: Causal relation diagram for automated driving.

8.2 CONCLUSIONS

This subsection contains answers on the remaining sub questions and answers finally the main research question.

The first data-analytics related sub question is: *Are Dutch citizens willing to pay the same amount of money for reducing travel time in an AV as for reducing travel time in a conventional car and what are the differences?*. The simple answer to this question is no. The discrete choice models indicate that people that use an AV in which it is possible to perform working activities have a lower mean VOTT compared to the VOTT of conventional car travellers. On the other hand, people travelling with an AV in which it is possible to have leisure time have a higher mean VOTT compared to conventional car travellers. Figure 8.2 shows the mean VOTT estimates per user group per model estimation. When the found VOTTs for car users, AV-office users and AV-leisure users are averaged the following values are found. The average VOTT of car travellers is around €8.04 per hour, the average VOTT of AV-office travellers is around €5.39 per hour (-33.0% compared to VOTT conventional car) and the average VOTT of AV-leisure users is around €10.84 per hour (+34.9% compared to VOTT conventional car). However, keep in mind that the given VOTTs are mean values and that heterogeneity exists within the VOTT of the different user groups.

The conclusion is that people who travel in an AV in which they can work are, on average, willing to pay less money to reduce their travel time compared to conventional car travellers, while people who travel in an AV in which they can only have leisure time are on average willing to pay more money to reduce their travel time compared to conventional car travellers.

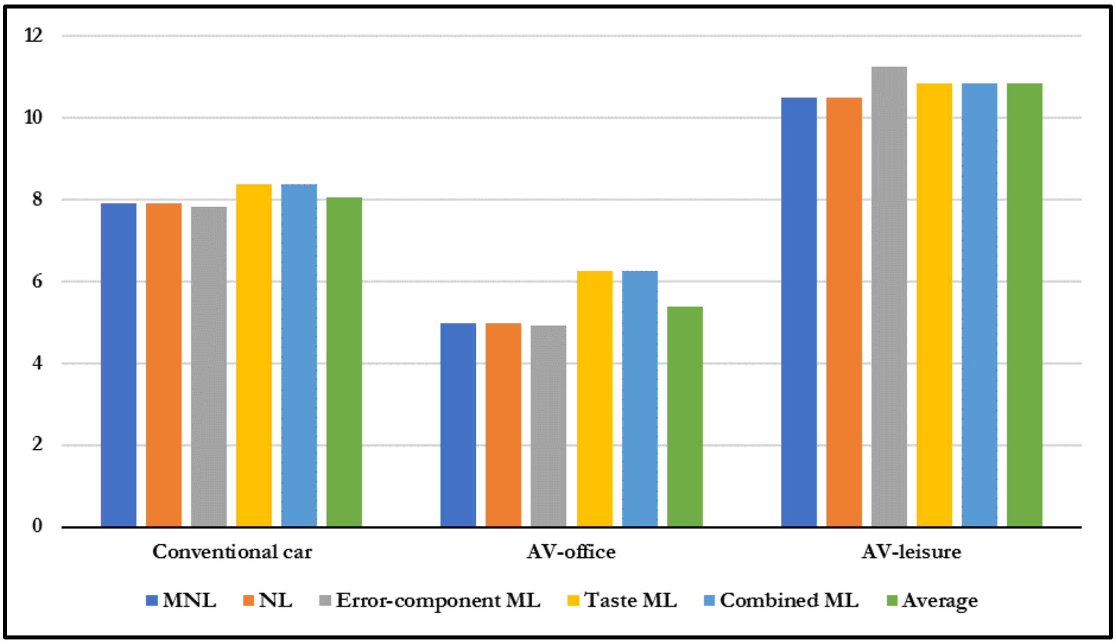

Figure 8.2: Mean VOTT estimates of the sample excluding non-traders (AV-case) in [€/hr].

The second unanswered sub question is: *Which activity does one prefer to do in an AV; work extra time or save time at the office?*. The model results indicate unanimously that if one chooses the AV with office interior he or she prefers to save time at the office (substituting travel time for time at home) over working additional time in the morning peak. So, it is concluded that if one chooses the AV-office one prefers to save time at the office over working additional time in order to get more spare days or more income.

Thirdly, the question: *Do attitudes towards automated driving have a significant influence on the mode choice?* can be answered. The model results imply that attitudinal factors have influence on the choice behaviour. A latent variable model was used to execute an exploratory factor analysis. The analysis showed that three main attitudinal factors were identified regarding automated driving. These factors were *conveniences of automated driving, (dis)trust in automated driving*, and *safety of automated driving*. These factors were included in the discrete choice models. The results showed the importance of attitudinal factors. The most important factor was conveniences of automated driving, since it had the highest parameter loading and was always significantly different from zero. A positive attitude towards the safety aspects of automated driving resulted also in a preference for AVs, but to lesser extent than the conveniences of automated driving. Not trusting the principles of automated driving tend people to choose a conventional car, however the marginal influence of this factor was least. Now, we can conclude that a positive or negative attitude towards automated driving does influence significantly the choice behaviour with regards to AVs.

The next sub question reads: '*Is a difference in trip appreciation observable in the case one is driven by a computer or by a human?*'. For answering this questions two exact same experiments are held: one with AVs as alternatives and one with chauffeur-driven cars as alternatives. For answering this question the results of the estimated models using data excluding non-traders is used, since it indicated more stable and consistent results. Figure 8.3 shows the mean VOTT estimates of the different traveller groups of the chauffeur-case. In the chauffeur-case the mean VOTT of chauffeur-driven office car users is always the lowest (€4.57 per hour) compared to the other travellers. In the AV-case, AV-office travellers have the lowest willingness-to-pay to reduce the travel time (€5.39 per hour). This VOTT is in line with the VOTT of AV-office users. So we can conclude that if one is able to work it does not matter whether he or she is driven by a human or a computer.

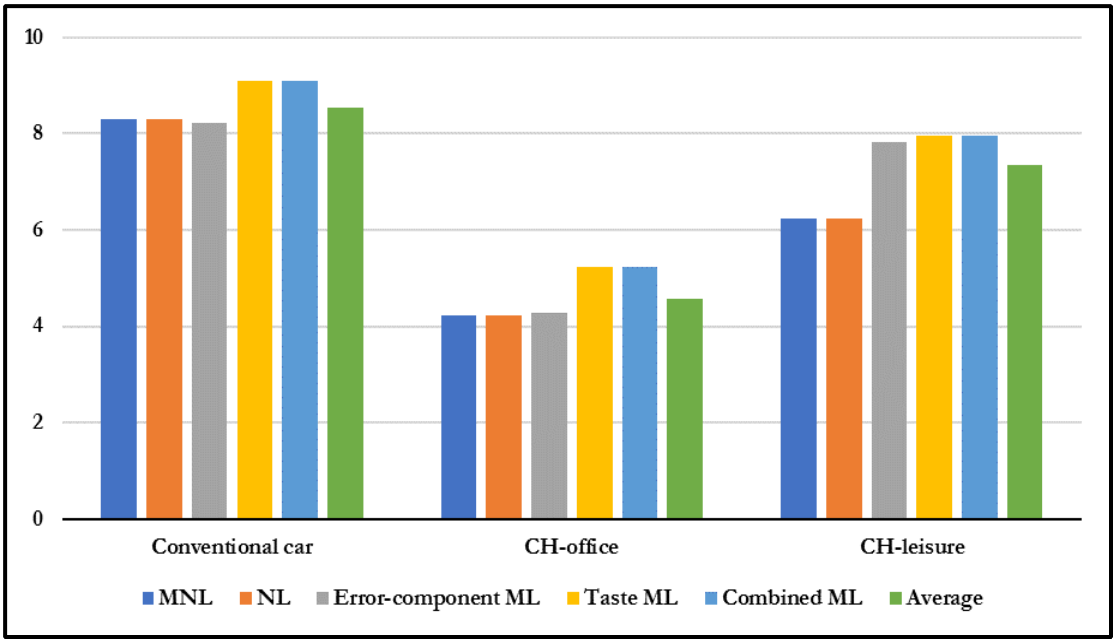

Figure 8.3: Mean VOTT estimates of the sample excluding non-traders (chauffeur-case) in [€/hr].

Conventional car travellers in the AV-case (€8.04 per hour) have on average a VOTT between the value of AV-office users and AV-leisure users (€10.84 per hour), whereas the average VOTT of conventional car drivers in the chauffeur-case is higher (€8.54 per hour) than the VOTT of the CH-leisure users (€7.61 per hour). However, the Welch's t-test indicated that the VOTT estimates of conventional car users and CH-leisure users do not differ significantly from each other in the MNL and error-component ML model. Still, a discrepancy is observed between the VOTT of the AV-leisure users and the CH-leisure users, indicating that automation is experienced differently when doing leisure activities while driving.

In the end we can draw the conclusion that it makes a difference if one is driven by a computer or by a human. Having leisure time is more positively experienced when driven by a chauffeur rather than driven by a computer compared to driving yourself. If one can work, the experience does not depend on being driven by a computer or by a human.

The last sub question is *Which factors influence the preference for automated driving?*. The model results indicate that travelling alone is preferred over travelling with companions in an AV. This behaviour is observed in the conventional car as well. People who are willing to work in an AV have a preference for AVs. The same behaviour is observed if people are able to work in a comfortable car with no vibrations and if people are willing to buy an AV. Furthermore, car-poolers prefer strongly an AV, while current BMT and car travellers prefer the conventional car. At last, there are indications that young people (<26 years) prefer an AV, while part-time employees, full-time employees, and elderly people (>60 years) tend to choose the conventional car. The non-trader analyses implied that almost half of respondents that are retired, 'other' employed, older than 60 years old, and/or lower educated are non-traders, whereas 66.7% of the primary school educated respondents were respondents. Almost all non-traders chose always the conventional car.

In the end, it is concluded that socio-demographic variables do influence the choice behaviour regarding automated driving. Mainly individuals who car-pool, are able to work in an AV, are willing to work in an AV and are willing to buy an AV favour automated vehicles. On the other side, respondents who are lower educated, older, retired and/or 'other' employed have a preference for the conventional car.

Now all sub questions have been answered an answer can be formulated for the main research question. The main research question of this study was:

How do full-automated vehicle users experience a trip compared to conventional car users for the trip purpose home-to-work in the Netherlands?

In five of the twelve choice tasks the conventional car alternative achieved an absolute majority (≥50% chosen). In total 56% of the choices opted for an AV alternative, thus there is a potential for automated driving in the Netherlands. A very good indicator of trip experience is the willingness-to-pay for travel time reduction. It is concluded that the willingness-to-pay (WTP) for travel time reduction for people travelling with an AV with office interior is approximately 33% lower compared to people travelling with a conventional car. This means that the disutility of travel decreases when using an AV-office thus that a journey in an AV-office is experienced better compared to a trip in a conventional car in the morning. Furthermore, a higher WTP to reduce travel time is observed for AV with leisure interior travellers with respect to conventional car travellers (± 35% higher). This means that people who are travelling in an AV-leisure in the morning peak experience their trip worse compared to conventional car users. At last, young people, people who are able and willing to work in an AV, and people with a positive attitude towards AVs tend to experience more utility from a trip in an AV than from a trip in a conventional car.

8.3 RECOMMENDATIONS

The last subsection of this report is devoted to recommendations. It is already mentioned that this study is a first exploration in how the VOTT will develop if an AV is used a main mode. A first recommendation is to conduct a study with a larger sample than this sample to determine more precise VOTT estimates for AV travellers. This sample, of 252 respondents, was quite oversampled in the age categories 50-59 years (10.4% point), 60-69 years (12.2% point), and in occupation category other (26.4% point). Besides 29.4% of the respondents showed non-trading behaviour.

- **Recommendation 1**: Conduct a more extended research with a larger and more representable sample for the Dutch population

My second recommendation is about the research method. In this research mixed logit models are used to estimate the VOTT distributions of the three different traveller groups. Unfortunately, due time constraints only the normal distribution was applied, which has the disadvantage that for certain individuals positive travel time parameters were estimated. However, this distribution was easy to implement in the models and it provided a good insight in the distributions of the VOTT estimates. Still, using a lognormal distribution, triangular distribution or Johnson's S_B distribution take away the concern of estimating a positive travel time parameter. So my second recommendation regards using another distributions.

- **Recommendation 2**: Make use of a 'closed' distribution like the lognormal distribution, triangular distribution or Johnson's S_B distribution in a future research about the distribution of the VOTT estimates.

My third recommendation regards the VOTT of AV-leisure users. This study indicates that the VOTT of AV-leisure users is higher compared to the VOTT of conventional car users. This result is not in line with the expectation. So, the third recommendation is to do an elaborated research to the VOTT of AV-leisure users.

- **Recommendation 3:** Do an elaborated research to the VOTT of AV-leisure users.

The fourth recommendation is about exploring the effects of travel time reliability when travelling with an automated vehicle. In the policy implications it came forward that this concept could be important for making a CBA when taking AVs into account. The concept of reliability is also implemented in current CBA studies, so my fourth recommendation is to do research about the value of travel time reliability for AV travellers.

- **Recommendation 4**: Do an exploratory research to the effects of travel time reliability for future AV users.

Furthermore, is was tested if longer travel times are more accepted when driving in an AV. However, it was not tested if the VOTT of an AV traveller is the same for having a longer trip due to more driven kilometres or due to being stuck in a traffic jam. Investigating if a difference is observable in these cases is a topic for further research.

- **Recommendation 5:** Conduct a research to explore if a difference in VOTT for AV travellers is observable due to a larger travel distance or due to congestion.

The sixth recommendation regards CBAs as well. In the policy recommendations it became clear that the effects of a lower VOTT of AV-office users compared to conventional car on the benefits and costs of a CBA are unclear. The paragraph gave indications on how automated driving could influence CBAs. However, there is insufficient knowledge on how the VOTT of AV-users will influence Dutch CBAs. It is therefore recommended to do further research on the effects of automated driving on CBAs.

- **Recommendation 6:** Conduct a research to what extent the VOTT of AV-users influences the different component of a CBA.

Because automated driving could have a large impact on other modes of transport, like the train, it is recommended to do a research in what the modal split will be when AVs are included as modes of transport. The effect of a substitution of car travellers by AV travellers is totally different than the substitution of train travellers by AV travellers, and this requires other policies. Therefore, this study was limited to private AVs. It is imaginable that shared AVs have a big impact on the model split as well. So, my fourth recommendation is:

- **Recommendation 7**: Explore the impact of (shared) automated driving on existing modes of transport.

My last recommendation regards the level of automation of the vehicle. This study focussed on the VOTT of (level 5) privately owned full-automated vehicle travellers. However, this modality is (still) far away and futuristic. Before the full-automated vehicle will be driving on the Dutch roads, partial-automated vehicles will be around. Therefore, the VOTT could be different when using shared AVs. So, my last recommendation is to do more research to explore the VOTT of lower automation level (shared) vehicles.

- **Recommendation 8**: Explore the VOTT for users of level 1-, level 2- level 3- and level 4-(shared) AVs, since full-automated vehicles are still far away.

8.4 PERSONAL REFLECTION

The last paragraph contains the personal reflection on the process of the author of this thesis. In the beginning of the thesis I was afraid that the graduating process would be a real burden. Fortunately, at the end I can say that I was afraid for nothing.

From the first day on I had a great guidance and supervision of both dr ir. Gonçalo Homem de Almeida Correia and dr. Maaike Snelder. In the first few days I has some struggles in collecting enough literature to use as base for my research. However, after I collected enough material it became quite clear what I was going to do.

The week before the kick-off meeting the committee was changed. Dr. Jan Anne Annema withdrew himself and was replaced by dr. ir. Sander van Cranenburgh, which was, with the knowledge of this moment, a very useful adaptation.

After the kick-off meeting I fully focussed on completing the survey as soon as possible. In finalising the final survey as soon as possible I made a mistake when making the prior-estimation survey. I did not ask for socio-demographic data of the respondents of prior-estimation survey. This resulted in not knowing the descriptive statistics of the sample, so next time I would definitely not forget that.

Another aspect that I would do differently regards the distribution of the final surveys. Two online panels were used. It took a long time from the moment the final surveys were completed and the moment respondents were able to fill out the survey. Almost all conversations went through mail contact, which delays the process. I would definitely recommend to call with your contact rather than mail your contact. Because my experience is that calling a contact results in more action than mailing with your contact.

I would do the modelling phase exactly the same if a next time would occur. Before I got the data I already wrote the scripts of the discrete choice models. Maybe a next time I would write the syntax in the python BIOGEME language rather than the bison BIOGEME language. Regarding the modelling, I have to admit that I underestimated the duration of the mixed logit simulations.

Initially, the idea was to use latent class modelling as well. However, modelling this types of models did not go well, and the results were very hard to interpret. So, in the end I decided to not use this modelling technique anymore. This is, from my perspective, experienced as a shortcoming of this work.

Overall I can say that I managed the graduation project quite well. During the time I kept updating my final thesis, so I did not have to stress about completing everything on time. Because I was collecting data in February I was not able to continue my thesis. During this period I went for a holiday to Ireland and Costa Rica. I recommend every graduate student to take a small break in the middle of the graduation project. During this holiday I emptied my head and rested a lot such that I was ready to finish my thesis when I came home! This holiday delayed the graduation process with one month. Ultimately, I was lucky to work with intelligent and motivated colleagues at TNO, which were always willing to help me when I got stuck.

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APPENDICES

APPENDIX A: PRIOR-ESTIMATION SURVEY

This appendix includes the prior-estimation study. The survey is distributed in Dutch to family, friends, and colleagues of both the researcher and the first supervisor (Dr. ir. G. Homem de Almeida Correia). First a description is given what this survey is about. Then some additional information is given about automated driving and the provided options. Subsequently, one attribute is explained. At last, the 12 choice tasks are given. The survey is constructed via Google Forms (Google, n.d.).

DESCRIPTION BEFORE FILLING IN THE CHOICE TASKS

Deze enquête gaat over het meten van de voorkeuren voor vervoersmiddelen.

12 vragen worden gesteld waarbij het de bedoeling is dat je jouw voorkeursmodaliteit aankruist.

Je kan kiezen uit 3 opties: de gewone brandstofstofauto, het automatische voertuig (AV) met kantoor interieur en het automatische voertuig met vrije tijd/plezier interieur.

In een automatisch voertuig, ook wel bekend als de zelfrijdende auto, hoef je zelf niet op de weg te letten; het AV rijdt zichzelf naar de door jou opgegeven locatie.

Een AV is te vergelijken met een auto met een gratis chauffeur die altijd beschikbaar voor je is. De auto wordt gereden en jij hebt de mogelijkheid andere activiteiten te ondernemen.

In een kantoor-AV moet je je voorstellen dat je in staat bent om te werken. Je kan je laptop kwijt, er is elektriciteit, Wi-Fi etc.

In een vrijetijds-AV moet je je voorstellen dat je er op een comfortabele manier je vrije tijd kan besteden. Je kunt een dutje doen, een boek lezen, bellen, film kijken, quality time hebben met vrienden en/of familie etc.

Als laatste, in de kantoor-AV kan je twee verschillende activiteiten ondernemen:

- Werkt extra tijd: je verdient meer geld, omdat je meer uren werkt naast je normaal aantal contracturen.

- Bespaart tijd op kantoor: je werkt evenveel uur, maar in plaats van alle werktijd op kantoor werken, werk je ook in het AV. Je ruilt hierbij reistijd in voor extra tijd thuis.

Elke trip is een enkele reis.

Alvast bedankt voor het invullen!

Erwin

PRIOR-ESTIMATION SURVEY – CHOICE TASKS

Table 0.1: Choice sets for prior estimation.

Scenario 1 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	40 minutes	20 minutes	40 minutes
Travel costs	€ 7.50	€ 7.50	€ 4.50
Walking time	6 minutes	0 minutes	0 minutes
Activity	Drive	Work extra time	Do whatever you want
Scenario 2 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	20 minutes	40 minutes	40 minutes
Travel costs	€ 6.00	€ 4.50	€ 4.50
Walking time	3 minutes	0 minutes	0 minutes
Activity	Drive	Save time at the office	Do whatever you want
Scenario 3 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	30 minutes	40 minutes	30 minutes
Travel costs	€ 4.50	€ 6.00	€ 7.50
Walking time	9 minutes	0 minutes	0 minutes
Activity	Drive	Work extra time	Do whatever you want
Scenario 4 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	40 minutes	20 minutes	20 minutes
Travel costs	€ 7.50	€ 4.50	€ 6.00
Walking time	9 minutes	0 minutes	0 minutes
Activity	Drive	Save time at the office	Do whatever you want
Scenario 5 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	20 minutes	40 minutes	40 minutes
Travel costs	€ 7.50	€ 4.50	€ 6.00
Walking time	3 minutes	0 minutes	0 minutes
Activity	Drive	Work extra time	Do whatever you want
Scenario 6 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	40 minutes	20 minutes	30 minutes
Travel costs	€ 7.50	€ 6.00	€ 4.50
Walking time	6 minutes	0 minutes	0 minutes
Activity	Drive	Work extra time	Do whatever you want
Scenario 7 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	40 minutes	30 minutes	20 minutes
Travel costs	€ 4.50	€ 7.50	€ 7.50
Walking time	3 minutes	0 minutes	0 minutes
Activity	Drive	Save time at the office	Do whatever you want
Scenario 8 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	20 minutes	30 minutes	30 minutes
Travel costs	€ 6.00	€ 7.50	€ 6.00
Walking time	9 minutes	0 minutes	0 minutes
Activity	Drive	Save time at the office	Do whatever you want
Scenario 9 of 12			

	Car	AV with office interior	AV with leisure interior
Travel time	30 minutes	20 minutes	40 minutes
Travel costs	€ 6.00	€ 7.50	€ 4.50
Walking time	6 minutes	0 minutes	0 minutes
Activity	Drive	Work extra time	Do whatever you want
Scenario 10 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	30 minutes	40 minutes	20 minutes
Travel costs	€ 7.50	€ 4.50	€ 7.50
Walking time	6 minutes	0 minutes	0 minutes
Activity	Drive	Work extra time	Do whatever you want
Scenario 11 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	20 minutes	30 minutes	30 minutes
Travel costs	€ 4.50	€ 7.50	€ 6.00
Walking time	9 minutes	0 minutes	0 minutes
Activity	Drive	Save time at the office	Do whatever you want
Scenario 12 of 12			
	Car	**AV with office interior**	**AV with leisure interior**
Travel time	30 minutes	30 minutes	20 minutes
Travel costs	€ 4.50	€ 7.50	€ 7.50
Walking time	3 minutes	0 minutes	0 minutes
Activity	Drive	Save time at the office	Do whatever you want

APPENDIX B: FINAL SURVEY

This appendix consists the final surveys distributed to panels. The surveys are in Dutch.

FINAL SURVEY – WELCOME NOTE & AIM OF RESEARCH (DUTCH)

WELCOME NOTE

Geachte deelnemer,

De enquête bestaat uit drie delen. Het eerste gedeelte bevat 12 keuzesets waarbij u uw voorkeursmodaliteit moet aankruisen. Het tweede deel van de enquête bevat stellingen waarbij u moet aangeven in hoeverre u het (on)eens bent met deze stellingen. In het laatste deel worden algemene vragen gesteld over uw huidige situatie.

Het invullen van de enquête neemt ongeveer 7,5 minuten in beslag.

Alvast bedankt voor het invullen!

AIM OF RESEARCH

Deze enquête heeft het doel om meer inzicht te krijgen naar de voorkeuren voor auto's die gereden worden door een chauffeur / voorkeuren voor zelfrijdende auto's. De informatie wordt gebruikt voor een afstudeerproject van de Technische Universiteit Delft in samenwerking met TNO.

FINAL SURVEY – PART I: CHOICE TASKS

INTRODUCTION PART I

Het eerste gedeelte van de enquête bestaat uit 12 keuzesets waarbij u uw voorkeursmodaliteit moet aankruisen.

Per keuzeset zijn drie alternatieven gedefinieerd: de conventionele brandstofauto, de auto met gratis chauffeur met kantoorinterieur en de auto met gratis chauffeur met vrijetijdsinterieur.

In een kantoor-auto moet u zich voorstellen dat het interieur u in staat stelt om te kunnen werken. U kunt uw laptop kwijt, er is elektriciteit beschikbaar, er is Wi-Fi etc.

In een vrijetijds-auto moet u zich voorstellen dat het interieur u in staat stelt om op een comfortabele manier uw vrije tijd te besteden. Zo kunt u een dutje doen, een boek lezen, bellen, quality time hebben met vrienden en/of familie, een film kijken etc.

Tenslotte kunt u in de kantoor-auto op twee verschillende manieren werken:

- Extra werken: u kunt extra uren werken, omdat de reistijd in de auto nu ook als werktijd gebruikt kan worden. U kunt meer geld of meer vrije dagen verdienen, omdat u meer uren maakt dan uw normale aantal contracturen.

- Tijdbesparing op kantoor: In totaal werkt u evenveel uur als nu, maar een deel van alle werktijd is in de auto in plaats van volledig op kantoor. U ruilt hierbij reistijd in voor extra tijd thuis.

Elke keuzeset betreft een enkele reis van huis naar werk.

CHOICE SETS PART I

Table 0.2: Choice sets final survey. AV = automated vehicle, CWC = Car with chauffeur.

Scenario 1 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	15 minutes	45 minutes	30 minutes
Travel costs	€4.50	€4.50	€7.50
Walking time	6 minutes	0 minutes	0 minutes
Travel companions	Family and/or friends	Family and/or friends	Alone
Activity	Driving	Work extra time	Do whatever you want
Scenario 2 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	30 minutes	30 minutes	15 minutes
Travel costs	€6.00	€4.50	€7.50
Walking time	2 minutes	0 minutes	0 minutes
Travel companions	Alone	Alone	Family and/or friends
Activity	Driving	Save time at the office	Do whatever you want
Scenario 3 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	45 minutes	45 minutes	45 minutes
Travel costs	€4.50	€7.50	€4.50
Walking time	6 minutes	0 minutes	0 minutes
Travel companions	Family and/or friends	Alone	Family and/or friends
Activity	Driving	Work extra time	Do whatever you want
Scenario 4 of 12			
	Car/CWC	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	15 minutes	30 minutes	45 minutes
Travel costs	€6.00	€7.50	€4.50
Walking time	2 minutes	0 minutes	0 minutes
Travel companions	Family and/or friends	Alone	Family and/or friends
Activity	Driving	Work extra time	Do whatever you want
Scenario 5 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	45 minutes	15 minutes	15 minutes
Travel costs	€7.50	€6.00	€4.50
Walking time	4 minutes	0 minutes	0 minutes
Travel companions	Alone	Family/friends	Alone
Activity	Driving	Save time at the office	Do whatever you want
Scenario 6 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	45 minutes	15 minutes	45 minutes
Travel costs	€4.50	€6.00	€7.50
Walking time	2 minutes	0 minutes	0 minutes
Travel companions	Family and/or friends	Alone	Family and/or friends
Activity	Driving	Work extra time	Do whatever you want
Scenario 7 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	15 minutes	15 minutes	30 minutes
Travel costs	€7.50	€7.50	€4.50
Walking time	4 minutes	0 minutes	0 minutes
Travel companions	Family and/or friends	Alone	Family and/or friends
Activity	Driving	Save time at the office	Do whatever you want
Scenario 8 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**

Travel time	30 minutes	45 minutes	30 minutes
Travel costs	€7.50	€6.00	€4.50
Walking time	4 minutes	0 minutes	0 minutes
Travel companions	Alone	Family and/or friends	Alone
Activity	Driving	Work extra time	Do whatever you want
Scenario 9 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	30 minutes	30 minutes	15 minutes
Travel costs	€6.00	€4.50	€7.50
Walking time	6 minutes	0 minutes	0 minutes
Travel companions	Family and/or friends	Family and/or friends	Alone
Activity	Driving	Save time at the office	Do whatever you want
Scenario 10 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	15 minutes	15 minutes	30 minutes
Travel costs	€7.50	€7.50	€6.00
Walking time	2 minutes	0 minutes	0 minutes
Travel companions	Alone	Family and/or friends	Alone
Activity	Driving	Save time at the office	Do whatever you want
Scenario 11 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	30 minutes	45 minutes	45 minutes
Travel costs	€6.00	€6.00	€6.00
Walking time	6 minutes	0 minutes	0 minutes
Travel companions	Alone	Alone	Family and/or friends
Activity	Driving	Save time at the office	Do whatever you want
Scenario 12 of 12			
	Car	**AV/CWC with office interior**	**AV/CWC with leisure interior**
Travel time	45 minutes	30 minutes	15 minutes
Travel costs	€4.50	€4.50	€6.00
Walking time	4 minutes	0 minutes	0 minutes
Travel companions	Alone	Family and/or friends	Alone
Activity	Driving	Work extra time	Do whatever you want

FINAL SURVEY – PART II: ATTITUDINAL STATEMENTS

INTRODUCTION PART II

In het tweede gedeelte van deze enquête worden u 18 stellingen getoond. U moet aangeven in hoeverre u het (on)eens bent met deze stellingen op een schaal van 1 tot 7, waarbij 1 helemaal oneens is en 7 helemaal eens is.

STATEMENTS PART II

Each question started with the sentence: 'In hoeverre bent u het eens met de volgende stelling: [statement]. Waarbij 1 helemaal oneens is en 7 helemaal eens is.'

1. I enjoy driving a car myself.
2. I would like to purchase an automated vehicle if it has better fuel efficiency than its conventional counterpart.
3. I trust that a computer can drive my car with no assistance from me.

4. I would be comfortable entrusting the safety of a close family member to an automated vehicle.
5. I think an individual requires a driving license before driving in an automated car.
6. I like it that I can be more productive on other tasks if I am riding in an AV.
7. I like it that I can delegate the driving to the automated driving system if I am due to certain circumstances not able to drive myself.
8. I like it that the automated car produces fewer pollutant emissions.
9. I like it that the car can park itself at cheaper parking spaces away from my destination.
10. I am afraid that the automated vehicle will malfunction.
11. I dislike the idea of automated driving.
12. I am afraid that the automated vehicle will not be fully aware of what is happening around him.
13. I do not like it that I do not have control of how the automated car drives.
14. I think that the automated driving system provides me more safety compared to manually driving.
15. I wish that automated vehicles were not around in the future.
16. I like it if I can recover control from the automated pilot if I do not like the way it is driving.
17. I like it that automated vehicles can adapt routes to avoid congestion.
18. I am afraid that I get motion sickness while riding in an automated vehicle.

FINAL SURVEY – PART III: SOCIO-DEMOGRAPHIC QUESTIONS

INTRODUCTION PART III

Het laatste gedeelte van de enquête bestaat uit 10 algemene vragen. Gelieve deze vragen zo nauwkeurig in te vullen.

Note: only ten questions are asked since the panel company could provide some socio-demographic data.

QUESTIONS PART III

1. Bent u in het bezit van een auto?
2. Bent u in het bezit van een rijbewijs?
3. Wat is uw voornaamste dagelijkse bezigheid?
4. Wat is momenteel uw jaarlijkse netto inkomen?
5. Is uw werk mogelijk uitvoerbaar in een comfortabele auto met internet en geen trillingen?
6. Bent u bereid te werken in een zelfrijdende auto?
7. Wat is momenteel uw deur-tot-deur reistijd?
8. Krijgt u een reisvergoeding voor de reiskosten die u maakt voor uw werk?
9. Wat is uw meest gebruikte vervoersmiddel?
10. Zou u, gegeven de informatie, overwegen een zelfrijdende auto te kopen voor dezelfde prijs als een normale auto?

FINAL SURVEY – THANK NOTE (DUTCH)

Dit is het einde van de enquête. Hartelijk dank voor het invullen van de enquête!

APPENDIX C: STANDARD ERRORS OF THE VOTT PARAMETERS OF THE PRIOR-ESTIMATION STUDY

For the computation of the standard error of the VOTT parameters the Delta method has been used. The delta method is suitable to give an approximation of the true standard error of a parameter (Daly et al., 2012). Since the VOTT is a ratio of two parameters the following formula found in van Cranenburgh & Chorus (2013) has been used:

Equation 41

$$\mathrm{S.E.}\left(\frac{\hat{\alpha}}{\hat{\beta}}\right) = \sqrt{\frac{1}{\hat{\beta}^2} \cdot \left[\mathrm{S.E.}\,(\hat{\alpha}) - \frac{2\hat{\alpha}}{\hat{\beta}} \cdot \mathrm{COV}(\hat{\alpha}, \hat{\beta}) + \left(\frac{\hat{\alpha}}{\hat{\beta}}\right)^2 \cdot \mathrm{S.E.}\,(\hat{\beta})^2\right]}$$

Where $\hat{\alpha}$ and $\hat{\beta}$ are respectively the estimated travel time parameter and travel costs parameter. The COV is the covariance between the travel time and the travel costs parameters. The outcomes of this calculation of the standard errors of the VOTT for car-, office-AV- and leisure-AV-users are shown in Table 0.3.

Table 0.3: Standard errors of the VOTTs estimated from the prior-estimation model.

	Value	*Std. error*
TT_car	-0.0708	0.0149
TC_car	-0.274	0.0922
Cov(TT_car, TC_car)	0.000399	
VOTT_car	0.258	0.0882
	Value	*Std. error*
TT_AVO	-0.108	0.0174
TC_AVO	-0.543	0.0932
Cov(TT_AVO, TC_AVO)	0.00129	
VOTT_AVO	0.199	0.0213
	Value	*Std. error*
TT_AVL	-0.128	0.015
TC_AVL	-0.582	0.122
Cov(TT_AVL, TC_AVL)	0.00121	
VOTT_AVL	0.220	0.0349

APPENDIX D: ELABORATION OF THE EXPLORATORY FACTOR ANALYSIS

This appendix shows the effectuation of the exploratory factor analysis and the final estimated results of the latent variable model. First the descriptive statistics of all attitudinal statements are shown in the next table.

Table 0.4: Descriptive statistics of the attitudinal variables.

	N	*Min*	*Max*	*Mean*	*Std. error*	*Std. dev.*	*Variance*
ST1	252	1	7	5.5357	0.10540	1.67318	2.800
ST2	252	1	7	4.1111	0.12325	1.95659	3.828
ST3	252	1	7	3.4881	0.11788	1.87132	3.502
ST4	252	1	7	3.2540	0.11509	1.82692	3.338
ST5	252	1	7	5.8413	0.09930	1.57628	2.485
ST6	252	1	7	4.0714	0.12130	1.92562	3.708
ST7	252	1	7	5.0357	0.11651	1.84960	3.421
ST8	252	1	7	5.5873	0.09683	1.53716	2.363
ST9	252	1	7	4.9802	0.11626	1.84553	3.406
ST10	252	1	7	5.4484	0.10567	1.67752	2.814
ST11	252	1	7	4.5595	0.12397	1.96798	3.873
ST12	252	1	7	5.1865	0.10582	1.67978	2.822
ST13	252	1	7	5.4762	0.09859	1.56513	2.450
ST14	252	1	7	3.7222	0.11052	1.75440	3.078
ST15	252	1	7	3.6825	0.12986	2.06141	4.249
ST16	252	1	7	6.0476	0.08045	1.27718	1.631
ST17	252	1	7	5.5198	0.09450	1.50020	2.251
ST18	252	1	7	2.7381	0.12260	1.94620	3.788

For analysing the 18 attitudinal indicators the software package SPSS has been used. For executing the EFA some steps were taken in the factor analysis pop-up, which are explained below.

- In the descriptives wizard: Tick the boxes 'coefficients', 'determinant', and 'KMO and Bartlett's Test of sphericity';
- In the extraction wizard: Pick the 'principal axis factoring' as method, next extract based on an Eigenvalue larger than 1, and display the rotated factor solution and scree plot;
- In the rotation wizard: Choose the varimax method for an orthogonal rotation, and;
- In the options wizard: Choose the exclude missing values listwise.

After the setup of the EFA, several iterations are executed before satisfying results were found. However, prior to the iterations some statistical tests must be conducted. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity are used to assess whether the obtained data is suitable for a factor analysis (Bartlett, 1950; Dziuban & Shirkey, 1974). Especially if the ratio respondents-variables is less than 1:5, the KMO is recommended. If the KMO index is greater than 0.5 it is considered suitable for factor analysis. Besides, the Bartlett's test of sphericity must be significant ($p < 0.05$) as well. (B. Williams, Onsman, & Brown, 2010).

Table 0.5 shows the outcomes of the KMO measure of sampling adequacy and the Bartlett's test of sphericity. Both tests proof (KMO > 0.5 and Bartlett's test sig $p < 0.05$) that the dataset is suitable for the factor analysis.

Table 0.5: Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericity.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.874
Bartlett's Test of Sphericity	Approx. Chi-square	1,652
	Degrees of freedom	55
	Significance	0.00

I. The first step after the starting iteration is to check whether indicators have a communality lower than 0.25. In the extraction column attitudinal indicator 18 has a communality of 0.219, so this indicator is eliminated and a second factor analysis has been executed.

II. In the second iteration all indicators have a communality higher than 0.25. A four-factor solution has been provided. Attitudinal indicator 1 has the lowest communality (0.304), and has a factor loading lower than 0.50 (0.495). Thus this indicator is excluded in the third iteration.

III. After the third iteration indicator 5 has a communality lower than 0.25 (0.186). So, this indicator was left out during the fourth iteration.

IV. In the fourth iteration all indicators have a communality above 0.25. Now a three-factor solution was given with several indicators having a factor loading lower than 0.50. It is chosen to exclude indicator 16, since it had the lowest factor loading (-0.369) and communality (0.302).

V. The fifth iteration gives a three-factor solution as well. All attitudinal factors have a communality score higher than 0.25 and all factors have a factor loading higher than 0.50. However, some factors have higher loadings on multiple factors. It is chosen to exclude indicator 6, since it has the lowest communality (0.541) of the factors that have multiple higher factor loadings.

VI. Iteration number six gives a three-factor solution with all factors having a higher communality than 0.25 and minimal one factor loading higher than 0.50. Two indicators have a factor loading of approximately 0.50. Since indicator 15 has the lowest communality of the two (0.548), this indicator is eliminated in a next iteration.

VII. Again, a three-factor solution is realised with all indicators having a communality higher than 0.25. One indicators loads higher than 0.5 on two factors, so indicator 2 is excluded from the eighth iteration.

VIII. The eights iteration produces a two-factor solution with all factors greater than 0.25. The Eigenvalues of the accepted factors are 5.469 and 1.655. However, the scree plot criterion mentions that from the component the line flattens out, the flattened factors should not be accepted. The flattening of the line does not start at factor three, but at factor four. Figure 0.1 shows that the line flattens from factor 4 instead of factor 3. Besides, the Eigenvalue of factor 3 is close to one: 0.972. For this reason, the ninth iteration includes a forced amount of three factors.

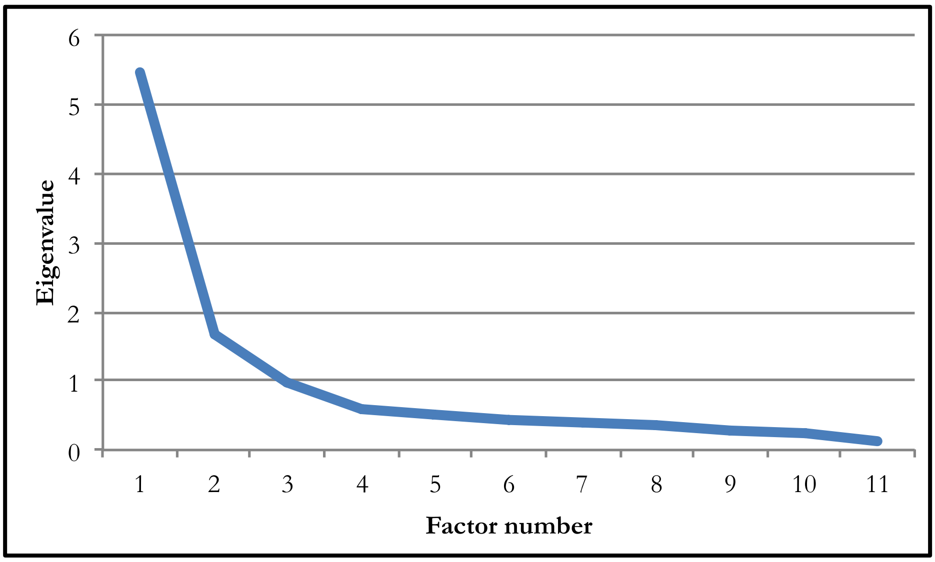

Figure 0.1: Scree plot iteration 8 and 9 of the exploratory factor analysis.

IX. The ninth iteration gives a three-factor solution with all indicators having a communality and factor loading respectively greater than 0.25 and 0.50. The indicators that have multiple loadings on factors score high on one factor and low (close to 0.30) on other factor(s).

The cumulative percentage of the variance of the initial Eigenvalues is 73.59%, of the extraction sums of squared loadings 64.37%, and of the rotation sums of squared loadings 64.37% as well. The last table of this appendix gives the results of the final communalities of the variables.

Table 0.6: Communalities final iteration latent variable model.

	Initial	*Extraction*
ST3	0.779	0.849
ST4	0.795	0.876
ST7	0.530	0.627
ST8	0.345	0.422
ST9	0.411	0.460
ST10	0.520	0.581
ST11	0.666	0.729
ST12	0.645	0.736
ST13	0.637	0.683
ST14	0.525	0.540
ST17	0.471	0.577

APPENDIX E: DESCRIPTIVE STATISTICS CHOICE SETS AV CASE

Table 0.7:Descriptive statistics choice sets AV-case.

				Choice set 1
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	176	36	40	252
Share	69,8%	14,3%	15,9%	100%
				Choice set 2
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	87	91	74	252
Share	34,5%	36,1%	29,4%	100%
				Choice set 3
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	137	51	64	252
Share	54,4%	20,2%	25,4%	100%
				Choice set 4
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	141	48	63	252
Share	56,0%	19,0%	25,0%	100%
				Choice set 5
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	71	38	143	252
Share	28,2%	15,1%	56,7%	100%
				Choice set 6
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	104	119	29	252
Share	41,3%	47,2%	11,5%	100%
				Choice set 7
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	91	85	76	252
Share	36,1%	33,7%	30,2%	100%
				Choice set 8
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	83	30	139	252
Share	32,9%	11,9%	55,2%	100%
				Choice set 9
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	76	99	77	252
Share	30,2%	39,3%	30,6%	100%
				Choice set 10
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	134	32	86	252
Share	53,2%	12,7%	34,1%	100%
				Choice set 11
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	156	53	43	252
Share	61,9%	21,0%	17,1%	100%
				Choice set 12
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	71	81	100	252
Share	28,2%	32,1%	39,7%	100%

APPENDIX F: RESULTS AV-CASE MNL MODEL

This appendix provides the results of the estimated multi nominal logit models. As mentioned earlier in this report, four different RUM models will be estimated per case (respectively AV and chauffeur). In this appendix the results of the MNL models for the AV-case are explained. Firstly, the variable coding and the utility functions are provided. Subsequently the parameter estimations are shown. Then, the model parameters will be interpreted and the VOTTs are calculated. The appendix ends with conclusions.

VARIABLE CODING & UTILITY FUNCTIONS

For this study two MNL models are estimated with the data from the AV-case. One model that includes only the variables that were introduced in the choice tasks (travel time, travel costs, walking time, activity, and travel company). The second model includes also socio-economic variables and latent factors to explain the behaviour of the decision maker better. Both models are estimated with two datasets from the AV-case: the full sample and the dataset without non-traders. The software package that is used for estimating the MNL models is BIOGEME (Bierlaire, 2003)

Before writing down the utility functions of the alternatives the variable coding is shown. Effect variable coding has been applied for the attribute levels of nominal variables and for the socio-economic variables. For each nominal variables having *X* attribute levels, *X-1* indicator variables are estimated. Table 0.8 shows the applied effect coding of all nominal variables that are estimated in the models.

Table 0.8: Effect coding used for attribute levels of nominal variables. IV = indicator variable.

Socio-economic variable	Category	IV 1	IV 2	IV 3	IV 4	IV 5
Travel company	Alone	-1				
	Family/friends	1				
Activity in AV with office interior	Save time at office	-1				
	Work extra time	1				
Gender	Female	-1				
	Male	1				
Car ownership	Yes	-1				
	No	1				
Able to work in AV	Yes	-1				
	No	1				
Willing to work in AV	Yes	-1				
	No	1				
Willing to buy an AV	Yes	-1				
	No	1				
Age	<26	-1	-1			
	26-60	0	1			
	>60	1	0			
Daily occupation	Work full-time	-1	-1	-1	-1	
	Work part-time	0	0	0	1	
	Student	0	0	1	0	
	Retired	0	1	0	0	
	Other	1	0	0	0	

Commonly used mode	Car	-1	-1	-1	-1	-1
	Car-pool	0	0	0	0	1
	Train	0	0	0	1	0
	BMT	0	0	1	0	0
	Bike	0	1	0	0	0
	None	1	0	0	0	0

The constant of each alternative reflects the average utility over all choice sets relatively to the reference alternative; the conventional car. The marginal value of each continuous variable represents the contribution of that component to the total utility. The identified continuous variables in this study are *travel time, travel costs* and *walking time*.

After explaining how the nominal variables are coded, the utility functions of both MNL models can be given. The three below mentioned equations are the utility functions of the conventional car, AV with office interior, and AV with leisure interior alternatives in the MNL model that only captures the SP attributes.

Equation 42

$$V_{CAR} = \alpha_{CAR} + \beta_{TT\_CAR} \cdot TT_{CAR} + \beta_{TC\_CAR} \cdot TC_{CAR} + \beta_{WT\_CAR} \cdot WT_{CAR} + \beta_{CO\_CAR} \cdot CO_{CAR}$$

Equation 43

$$V_{AVO} = \alpha_{AV} + \beta_{TT\_AVO} \cdot TT_{AVO} + \beta_{TC\_AVO} \cdot TC_{AVO} + \beta_{AC\_AVO} \cdot AC_{AVO} + \beta_{CO\_AV} \cdot CO_{AVO}$$

Equation 44

$$V_{AVL} = \alpha_{AV} + \beta_{TT\_AVL} \cdot TT_{AVL} + \beta_{TC\_AVL} \cdot TC_{AVL} + \beta_{CO\_AV} \cdot CO_{AVL}$$

Where the *a* represents the alternative specific constant, and *CAR*, *AVO* and *AVL* are abbreviations of conventional car, AV with office interior and AV with leisure interior. In this case the *a* of the conventional car alternative is fixed on zero. The parameters β_{TT}, β_{TC} and β_{CO} represent the alternative specific marginal utility parameters for travel time, travel costs and travel company respectively. The parameter β_{WT_CAR} is the marginal utility of the walking time for the conventional car alternative, and at last β_{AC_AVO} gives the marginal utility for the activity attribute in the AV with office interior.

The MNL model with additional socio-economic variables and latent factors differs in one utility function. All the socio-economic variables and the latent factors are added in the utility function of the *conventional car* alternative such that it measures the preference for the base alternative in comparison to the two AV alternatives. The utility function of the conventional car is altered in such a way that the new utility function is as follows:

Equation 45

$$\begin{aligned} V_{CAR} = \alpha_{CAR} &+ \beta_{TT\_CAR} \cdot TT_{CAR} + \beta_{TC_{CAR}} \cdot TC_{CAR} + \beta_{WT_{CAR}} \cdot WT_{CAR} + \beta_{CO} \cdot CO_{CAR} \\ &+ \beta_{ABLE} \cdot IV1_{ABLE} + \beta_{WIL} \cdot IV1_{WIL} + \beta_{BUY} \cdot IV1_{BUY} + \beta_{OWN} \cdot IV1_{OWN} \\ &+ \beta_{GENDER} \cdot IV1_{GENDER} + \beta_{AGE1} \cdot IV1_{AGE} + \beta_{AGE2} \cdot IV2_{AGE} + \beta_{OC1} \cdot IV1_{OC} \\ &+ \beta_{OC2} \cdot IV2_{OC} + \beta_{OC3} \cdot IV3_{OC} + \beta_{OC4} \cdot IV4_{OC} + \beta_{MODE1} \cdot IV1_{MODE} \\ &+ \beta_{MODE2} \cdot IV2_{MODE} + \beta_{MODE3} \cdot IV3_{MODE} + \beta_{MODE4} \cdot IV4_{MODE} + \beta_{MODE5} \\ &\cdot IV5_{MODE} + \beta_{CONV} \cdot CONV + \beta_{TRUST} \cdot TRUST + \beta_{SAFETY} \cdot SAFETY \end{aligned}$$

The first five components are the marginal utilities of the SP attributes and the alternative specific constant, which is fixed on zero for the conventional car. Then, β_{ABLE}, β_{WIL}, β_{BUY}, β_{OWN} and β_{GENDER} represent the marginal utility parameters for respectively if one is able to work in an AV, if one is willing to work in an AV, if one is willing to buy an AV for the same price as a conventional car, if one owns a car, and gender. The parameters β_{AGEx}, β_{OCx} and β_{MODEx} are the marginal utility of the nominal variables age, daily occupation and commonly used transport mode. The latter three components of the utility function represents the marginal utility of the identified latent factors: *conveniences of automated driving*, *(dis)trust in automated driving*, and the *safety of automated driving*.

RESULTS BASE MNL MODELS

Table 0.9 shows the statistics of the estimated discrete choice MNL model that only includes the attributes of the choice tasks. In both models 10 parameters are estimated from which seven parameters are significant. Only coefficients having a p-value lower than 0.05 are incorporated in the final model. It appears that the model without the non-traders has a higher adjusted Rho-Square than the estimated model from the full sample, meaning that this model fits the data better. In general, a model with an adjusted Rho-Square smaller than 0.10 is qualified as a poor model.

Table 0.9: Statistics discrete choice MNL model estimation with only SP attributes.

	MNL with full sample	*MNL excl. non-traders*
Number of observations	3,024	2,136
Number of estimated parameters	11	11
Null log-likelihood	-3,322.204	-2,346.636
Final log-likelihood	-3,043.778	-2,053.661
Adjusted Rho-Square	0.080	0.120

Table 0.10 and Table 0.11 show the estimation results of the MNL model from both datasets. In both model estimations the ASC for the AV, and the walking time coefficient are not statistically significant and equal 0.00. This means that in this model no preference is observed for either the conventional car or an AV and that the walking time does not influence the (dis)utility of the conventional car alternative. The estimated model with the data leaving out the non-traders, shows a significant activity coefficient. The mode-specific time and costs coefficients in the estimated model including the non-traders are lower than in the second model.

Table 0.10: Estimation results of discrete choice MNL model only with SP attributes (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	0.52	0.459	1.13	0.26	0.456
Traveltime_AV_leisure	-0.0342	0.0043	-7.96	0.00	0.0285
Traveltime_AV_office	-0.0261	0.00461	-5.66	0.00	0.0277
Traveltime_car	-0.0265	0.00409	-6.48	0.00	0.0459
Travelcosts_AV_leisure	-0.266	0.0281	-9.47	0.00	0.00434
Travelcosts_AV_office	-0.338	0.0282	-11.98	0.00	0.00451
Travelcosts_car	-0.172	0.0459	-3.75	0.00	0.00416
Activity_AV_office*	-0.0764	0.0486	-1.57	0.12	0.0482
Travel_company_AV	-0.133	0.0301	-4.41	0.00	0.0305
Travel_company_car	-0.138	0.053	-2.61	0.01	0.0523
Walkingtime_car*	0.0283	0.0283	1	0.32	0.0281

** = not significant in a 95% confidence interval.*

The mode-specific time coefficient is most negative for the leisure-AV users in both model estimations, meaning that increasing the time in a leisure-AV is experienced more negatively than in the office-AV and the conventional car. An increase in travel time in an office-AV appears to be the least worse, but the difference in coefficient with the conventional car is negligible in the model estimation with all respondent's data. A possible explanation for the higher time coefficient value for the leisure-AV is that one prefers to have leisure time at home or at another physical locations rather than in an AV. A smaller time coefficient for the office-AV seems logically, since one is able to work in the AV making it less annoying if the travel time increases.

The travel costs (-0.20) and travel time (-0.031) parameter for car have similarities with values found by Yap et al. (2016) for the estimated model with the full sample. The marginal value of travel costs in the study by Yap et al. (2016) comes close to the cost parameter for car in the MNL (excl. non-traders) (-0.41). At last, the travel time parameter found by Yap et al. (2016) for automated vehicles is -0.084, which is much more negatively valued than the travel time coefficients found in these model. However, it must be address that Yap et al. (2016) used the AV as egress mode, while AVs here are used as main mode. The mode-specific travel time parameters by Artenze & Molin (2013) for car users (-0.079 and -0.036) are lower than the values found in this MNL model.

Table 0.11: Estimation results of discrete choice MNL model only with SP attributes (excl. non-traders).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	0.386	0.6	0.64	0.52	0.592
Traveltime_AV_leisure	-0.0595	0.00559	-10.64	0.00	0.00558
Traveltime_AV_office	-0.0396	0.00558	-7.09	0.00	0.00553
Traveltime_car	-0.0505	0.00547	-9.23	0.00	0.00573
Travelcosts_AV_leisure	-0.359	0.033	-10.87	0.00	0.0334
Travelcosts_AV_office	-0.476	0.0335	-14.19	0.00	0.0329
Travelcosts_car	-0.379	0.0643	-5.9	0.00	0.064
Activity_AV_office	-0.122	0.058	-2.11	0.04	0.0577
Travel_company_AV	-0.104	0.034	-3.05	0.00	0.0342
Travel company_car	-0.209	0.0705	-2.96	0.00	0.0682
Walkingtime_car*	0.018	0.0371	0.49	0.63	0.0377

** = not significant in a 95% confidence interval.*

Regarding travel costs, it seems that the most disutility is experienced by office-AV users in both models. The least disutility from a one-euro increase in travel costs is experienced in the conventional car in the model from the full sample. Two mode-specific coefficients are estimated for the travel companions attribute; one coefficient for the car alternative and one for the AV alternatives. A model has been estimated with three travel company coefficients, but in this case only the car alternative parameter was statistically significant. Apparently, having travel companions is experienced more negatively when driving a normal car. Welch's t-test is used to determine whether the mode-specific travel company coefficients differ significantly of each other. Welch's t-test is a derivative of the Student's t-test and is more reliable when the samples have unequal variances and samples (Welch, 1947). However, by comparing parameters within the same sample size, dividing by the sample size is not relevant. So, the equation of Welch's t-test is adapted as follows (Welch, 1938):

Equation 46

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{s_1^2 + s_2^2}}$$

Where X_1 and X_2 are the sample means, and s_1 and s_2 are the sample variances. To compute the associated degrees of freedom, the Welch-Satterthwaite equation is used. This equation approximates the degrees of freedom (v):

Equation 47

$$v \approx \frac{\left(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}\right)^2}{\frac{s_1^4}{N_1^2 v_1} + \frac{s_2^4}{N_2^2 v_2}}$$

Where v is equal to $N-1$, and N_x are the sample sizes. The table of critical t-values is used to determine if a difference in parameters is statistically significant. With a t-value of 1.34 with approximately 255 degrees of freedom, it can be concluded that the parameters do not differ from each other in the case where non-traders are excluded. So, travelling alone in either an AV or a conventional car is valued the same. The difference in parameter found in the estimated model with all respondents is not statistically significant (t-value: 0.08, df: 398). This result could be expected since the coefficients are almost equal. At last, the estimated model (excl. non-traders) provides us information about the preferences of the type of activity one performs in an office-AV. Save time at the office (substituting travel time for time at home) is, given its effect coding (-1), preferred over working extra time. Thus, given this estimated model it appears that one prefers spare time than working extra.

Since this study is about how people will appreciate their trips in a full-automated vehicle, the VOTT will be evaluated. It is assumed that the coefficients of the travel time and the travel costs are linear such that the VOTT can be calculated making use of the ratio of these two coefficients. To calculate the standard errors of the ratios, the Delta method is used again (Daly et al., 2012). The equation to calculate the standard error of the three VOTTs, the equation of van Cranenburgh & Chorus (2013) has been used (see 0). This method has also been applied to calculate the standard errors of the found VOTTs of the *prior-estimation* study. Table 0.12 shows an overview of the estimated VOTTs.

Table 0.12: The VOTTs estimated from the MNL models only with SP attributes.

Full sample MNL	*Value*	*Std. error*	*Value*
VOTT Car	0.154 [€/min]	0.0335	9.24 [€/hr]
VOTT AV with office interior	0.077 [€/min]	0.0153	4.63 [€/hr]
VOTT AV with leisure interior	0.129 [€/min]	0.0209	7.71 [€/hr]
Excl. non-traders MNL			
VOTT Car	0.133 [€/min]	0.0181	7.99 [€/hr]
VOTT AV with office interior	0.083 [€/min]	0.0129	4.99 [€/hr]
VOTT AV with leisure interior	0.166 [€/min]	0.0209	9.94 [€/hr]

The standard errors of all VOTTs are acceptable small. The estimated value of time of the users of the AV with office interior is according expectation: lower than the VOTT for car users.

However, big differences are observed in the VOTT of car users and of leisure-AVs users. In the model that includes the full sample car drivers have the highest VOTT, where in the model that excludes non-trading the AV-leisure users have the highest VOTT. The VOTTs found for car drivers approach the values of Kouwenhoven et al. (2014) and Yap et al. (2016), which are €9.00 per hour and €9.30-9.90 per hour respectively.

A reason for the observation that one is willing to pay more money to reduce his/her travel time in an leisure-AV (MNL excl. non-traders) is that one prefers to have leisure time at home, a bar, a cinema and so on. Again, Welch's t-test has been used to determine whether the VOTTs statistically differ from each other. The results, shown in Table 0.13, indicate that the estimated VOTT ratio of the AV-leisure user is not significantly different from the car traveller's VOTT.

Table 0.13: Results Welch's t-test of the VOTTs within the estimated MNL models only with SP attributes.

Full sample MNL	*t-value*	*df.*	
VOTT Car – VOTT AVO	2.09	352	Significant
VOTT Car – VOTT AVL	0.65	421	Not significant
VOTT AVO – VOTT AVL	2.45	460	Significant
Excl. non-traders MNL			
VOTT Car – VOTT AVO	2.25	321	Significant
VOTT Car – VOTT AVL	1.18	346	Not significant
VOTT AVO – VOTT AVL	3.36	295	Significant

However, the last question that has to be answered is whether the VOTTs found in the different models are significantly different from each other. Welch's t-test is used again. Table 0.14 shows the results of Welch's t-test. There is no significant difference observed between the VOTT for users of the AV with office interior.

Table 0.14: Results Welch's t-test of the VOTTs between the estimated MNL models only with SP attributes.

	t-value	*df.*	
VOTT Car	8.31	403	Significant
VOTT AV with office interior	0.76	414	Not significant
VOTT AV with leisure interior	4.02	381	Significant

CONCLUSIONS BASE MNL MODELS

In this paragraph I try to draw conclusions from the estimated models. Altogether it can be concluded that these basic estimated MNL models provide insights in travel appreciation of automated driving compared to manually driven cars. First I draw conclusion from the MNL model estimated from the full sample data, subsequently of the MNL model estimated from the data that excluded the non-traders.

There is no preference observed for the an AV relative to the car. Despite the significant mode-specific travel company coefficients, no differences are observed in how decision makers experience travel company in a car or an AV. Additional travel time is experienced worse in the AV with leisure interior compared to the other alternatives. However, an increment of travel costs is experienced worst in the AV-office. Most important is that the VOTT for the users of the AV with office interior is significantly lower than the VOTT of the conventional car user, which confirms the expectation.

The MNL model (excl. non-trading) indicates that one gains less disutility from increased travel time in an AV with office interior in comparison to the conventional car. However, an increment in travel costs is perceived worse in the office-AV. Next, it appears that travelling alone is perceived more pleasant in both a normal car and an AV, however the utility gain/loss for car drivers is higher. Furthermore, this model implies that the VOTT is significantly lower for the users of the AV with office interior compared to the conventional car and the leisure-AV. On the other hand, the VOTT for users of the leisure-AV is considerable higher than the value found for car drivers. This was not according expectation.

RESULTS EXTENDED MNL MODELS

In an attempt to improve the model fitness of the above discussed MNL models they are extended with socio-economic variables and latent factors. First two models are estimated including all socio-economic variables. Then, per data set (full sample and data excl. non-traders) a new model is estimated with only the significant parameters. The results of the latter estimated models are discussed in this subsection.

In the case in which we added the socio-economic variables, the adjusted Rho-Square improves significantly using the dataset with all respondents as well as the dataset excluding the non-traders (see Table 0.15). In the elaborated MNL models 19 (different) parameters are estimated.. The adjusted Rho-Square is in both estimated models above 0.10, so the estimated models predict the data reasonably well.

Table 0.15: Statistics final discrete choice MNL models.

	MNL with full sample	*MNL excl. non-traders*
Number of observations	3,024	2,136
Number of estimated parameters	19	19
Null log-likelihood	-3,322.204	-2,346.636
Final log-likelihood	-2,614.156	-1,964.630
Adjusted Rho-Square	0.207	0.155

Both comprehensive MNL models fit the data better than the models that incorporated only the SP attributes. Eventually, 17 coefficients are significant in the two models. The estimation results are shown in Table 0.16 and Table 0.17. First the results of the estimated MNL model with all data are discussed followed by the model estimated from the data without non-traders.

Again, the ASC for the AVs is not significant, meaning that no preference is observed for AV with respect to the conventional car. An increase in travel time is worse experienced in the AV with leisure interior, and the least disutility from an increase in travel time is experienced in the AV-office. The differences in mode-specific travel time coefficients in this MNL model is greater than in the base MNL model. Again, an increment in travel costs is experienced worse in the AV with office interior followed up by the AV-leisure and the least in the conventional car. Given the effect coding for *activity in AV-office* and *travel company* it becomes clear that saving time at office (-1 * -0.114 = 0.114) and travelling alone is preferred. It is interesting to observe that if one is able to work in a vehicle with high comfort, internet and no vibrations (effect coded -1) one prefers an AV. The same behaviour is observed if a decision maker is willing to work in an AV, and if one is willing to purchase an AV if it is for sell for the same price as a conventional car. The observation that one prefers automated driving if one is willing to work in an AV is as expected, because these persons benefits most from the possibilities of automated driving. The coefficient values of the significant latent factors are also as expected. If one acknowledges the conveniences of an AV (-0.718), one does not prefer the car. The same can be concluded if a decision maker is convinced that automated driving is safer than driving a car yourself (-0.303). The positive parameter (0.246) for *trust in automated driving* is logical as well, if a decision maker does not trust an AV, it prefers a manually driven car. The last two coefficients that appear to be significant are two *commonly used mode* coefficients. If one does carpooling, he or she prefers an AV above the conventional car. However, if one travels mostly with bus/tram/metro, it is preferred to make use of the conventional car. At last, if one drives a car it is preferred to use the conventional car as well, because 1.04 * -1 + -1.73 * -1 is 0.69.

The travel time and travel costs parameters found in this model do not differ much from the values (TT: -0.031, TC: -0.20) found by Yap et al. (2016). The travel costs parameter of the AV-office is almost similar to the travel costs marginal value found by Yap et al. (2016), which is -0.41. Again, the mode-specific time parameter for travel time found by Yap et al. (2016) is much more negative (-0.84). Both the travel time and travel costs parameters of Arentze & Molin (2013) are more negative than the values found in this model.

Table 0.16: Estimation results of final discrete choice MNL model (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	0.762	0.518	1.47	0.14	0.51
Traveltime_AV_leisure	-0.0445	0.00483	-9.21	0.00	0.00491
Traveltime_AV_office	-0.0296	0.00478	-6.19	0.00	0.00468
Traveltime_car	-0.0380	0.00476	-7.98	0.00	0.00496
Travelcosts_AV_leisure	-0.280	0.0289	-9.68	0.00	0.0295
Travelcosts_AV_office	-0.385	0.0300	-12.83	0.00	0.0295
Travelcosts_car	-0.260	0.0525	-4.96	0.00	0.0515
Activity_AV_office	-0.114	0.0512	-2.23	0.03	0.0498
Travel_company_AV	-0.103	0.0307	-3.37	0.00	0.0307
Travel_company_car	-0.188	0.0607	-3.10	0.00	0.0603
Walkingtime_car*	0.0523	0.0323	1.62	0.10	0.0333
AbleToWork_car	0.125	0.0540	2.32	0.02	0.0553
WillingToWork_car	0.319	0.0618	5.16	0.00	0.0617
Buy-AV_car	0.371	0.0629	5.90	0.00	0.0608
Convenience_car	-0.718	0.0619	-11.61	0.00	0.0597
Safety_car	-0.303	0.0556	-5.45	0.00	0.0556
Trust_car	0.246	0.0535	4.60	0.00	0.0538
Mode_BMT_car	1.04	0.1970	5.28	0.00	0.1960
Mode_carpool_car	-1.73	0.2440	-7.10	0.00	0.2400

** = not significant in a 95% confidence interval.*

Next are the interpretations of the results of the estimated MNL model excluding non-traders data. It appears that there is no unobserved preference for automated driving, since the ASC is not significant. The mode-specific time coefficients tell us that an increase in travel time gives provides most disutility in the AV-leisure (-0.064) and least in the AV with office interior (-0.056). An increase in travel costs is experienced more negatively in an AV-office (-0.495) compared to the car or the AV with leisure interior (-0.365). Again, it is preferred to save time at the office instead of working extra time (-0.138). Travelling with others is experienced very negatively in comparison to the AV alternatives. A distinction between travelling with company for different AVs is not significant. Travelling alone is highly preferred by car drivers. A clear explanation for this phenomenon cannot be given. Regarding the socio-economic variable age, only the first indicator variable is significant for car drivers. This means that travellers older than 60 years value driving a car themselves marginally more positively (0.336), and that people <26 years value a manually driven car marginally more negatively (-0.336). People in the age category 26-60 their marginal value for the car alternative equals 0.00. If one is willing to work in an AV and if one is willing to buy an AV the car alternative is marginally valued negatively (respectively -0.294 and -0.409). Only the *conveniences of automated driving* latent variable is statistically significant. If a decision values the convenience of automated driving positively, it does prefer an AV. Two *daily occupation* indicators are statistically significant. If one is working part-time it marginally values the conventional car more positively (0.296), however if one is retired the car is valued marginally more negatively (-0.621). The marginal valuation of students and other equals 0.00, whereas a full-time worker values a manually driven car very positively (0.296 * -1 + -0.621 * -1 = 0.325). At last, two indicators of *commonly used mode* are significant. The conventional car is valued marginally positively by BMT users (0.854), whereas car-poolers value the car alternative very negatively (-1.45). The marginal valuation of bike- and train users is 0.00. Current car users value the car alternative marginally positively (0.854 * -1 + -1.45 * -1 = 0.596) with respect to automated vehicles.

When comparing the marginal utility parameters of travel time and travel costs with other studies, it is observed that as well the time and the costs parameters found by Yap et al. (2016) for car users are half the values in this study. The time parameter for AV-users found by Yap et al. (2016) is still more negative (-0.084) than the ones estimated with this MNL model. The travel cost parameter of Yap et al (2016) is -0.41, which is in between the estimated values of this MNL model. The car-specific travel time coefficient is between the values found by Arentze & Molin (2013) (-0.079 and -0.036).

Table 0.17: Estimation results of final discrete choice MNL model (excl. non-traders).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	0.674	0.627	1.07	0.28	0.616
Traveltime_AV_leisure	-0.0637	0.00578	-11.02	0.00	0.00577
Traveltime_AV_office	-0.0410	0.00565	-7.25	0.00	0.00562
Traveltime_car	-0.0559	0.00578	-9.67	0.00	0.00602
Travelcosts_AV_leisure	-0.365	0.0334	-10.92	0.00	0.034
Travelcosts_AV_office	-0.495	0.0343	-14.45	0.00	0.0335
Travelcosts_car	-0.424	0.0669	-6.34	0.00	0.0662
Activity_AV_office	-0.138	0.0588	-2.35	0.02	0.0582
Travel_company_AV	-0.0923	0.0342	-2.70	0.01	0.0343
Travel_company_car	-0.232	0.0731	-3.17	0.00	0.0708
Walkingtime_car*	0.029	0.0386	0.75	0.45	0.0395
Age1_car	0.336	0.112	3.01	0.00	0.112
WillingToWork_car	0.294	0.0635	4.63	0.00	0.0617
Buy-AV_car	0.409	0.0668	6.11	0.00	0.0659
Convenience_car	-0.30	0.0821	-3.65	0.00	0.0815
DO_retired_car	-0.621	0.155	-4.00	0.00	0.152
DO_workpt_car	0.296	0.111	2.66	0.01	0.110
Mode_BMT_car	0.854	0.214	3.99	0.00	0.200
Mode_carpool_car	-1.45	0.277	-5.23	0.00	0.258

** = not significant in a 95% confidence interval.*

In the last two indentions the results of both final MNL models are discussed. The next step in the result discussion is the evaluating the value of travel times that these models bring forward. Table 0.18 gives an overview of the VOTTs estimated from the final MNL models. In both cases the VOTT for users of the AV with office interior is lower than that VOTT of car users. This results is according expectation. The standard errors of the VOTTs from the non-traders case are lower than the all respondents dataset. However, all the standard errors are reasonable low. The VOTT of AV-leisure users is in all estimation the highest, meaning that these people are willing to pay more money to reduce their travel time.

Table 0.18: The VOTTs estimated from the final MNL models.

Full sample MNL	*Value*	*Std. error*	*Value*
VOTT Car	0.146 [€/min]	0.0242	8.77 [€/hr]
VOTT AV with office interior	0.077 [€/min]	0.0138	4.61 [€/hr]
VOTT AV with leisure interior	0.159 [€/min]	0.0232	9.54 [€/hr]
Excl. non-traders MNL			
VOTT Car	0.132 [€/min]	0.0165	7.91 [€/hr]
VOTT AV with office interior	0.083 [€/min]	0.0125	4.97 [€/hr]
VOTT AV with leisure interior	0.175 [€/min]	0.0214	10.47 [€/hr]

Next is has to be calculated if the found values in the models significantly differ from each other as well as whether the VOTTs between the models are significantly different. Welch's t-test has been used to compute this (Equation 46 and Equation 47). Table 0.19 shows the results of Welch's t-test. The Welch's t-test indicates that the VOTT estimates of car users and AV-leisure users do not differ significantly from each other in both models. All other VOTT estimates are significantly different.

Table 0.19: Results Welch's t-test of the VOTTs within the estimated final MNL models.

Full sample MNL	*t-value*	*df.*	
VOTT Car – VOTT AVO	2.49	398	Significant
VOTT Car – VOTT AVL	0.38	501	Not significant
VOTT AVO – VOTT AVL	3.04	408	Significant
Excl. non-traders MNL			
VOTT Car – VOTT AVO	2.37	330	Significant
VOTT Car – VOTT AVL	1.58	332	Not significant
VOTT AVO – VOTT AVL	3.69	285	Significant

The following table provides an overview to check whether the VOTTs found between the estimated models are significant. The outcome of the last Welch's t-test is that all the VOTTs are significant.

Table 0.20: Results Welch's t-test of the VOTTs between the estimated final MNL models.

	t-value	*df.*	
VOTT Car	7.30	428	Significant
VOTT AV with office interior	4.65	402	Significant
VOTT AV with leisure interior	7.17	399	Significant

CONCLUSIONS EXTENDED MNL MODELS

In the last part of this appendix conclusions are draw based on the estimated results of the finals MNL models. Given the adjusted Rho-Squares of both final MNL models it can be concluded that the final models predicts the behaviour of the decision makers better compared to the base models The improvements in adjusted Rho-Squares is as follows:

- *Full sample:* Base MNL model (0.080) vs. final MNL model (0.207)
- *Exclusive non-traders:* Base MNL model (0.120) vs. final MNL model (0.155)

It can be seen that the estimated model from the entire sample improved much, while the estimated model from the data without non-traders improved less extreme. The reason that the former models give such improvements could be that variables are added in the model that elucidates the behaviour of non-traders. An example could be the *convenience* parameter. In the estimated model from all respondents this coefficient is much higher than in the other model. It is likely that car non-traders do not recognise the conveniences of automated driving, which can be seen in the parameter value. Since the non-traders are included in the first model, this parameter is more extreme than in the latter case. First I will draw conclusions from the final MNL model estimated with the data from full sample, and secondly conclusions are drawn from the other MNL model.

As mentioned above it can be concluded that the model with socio-economic variables fits the data better than the base MNL model. Almost all marginal utility parameters show the expected positive of negative sign. My expectation was that BMT users tend to prefer AV, since it is more comfortable than travelling with public transport. An increase in travel time is most negatively experienced in the AV-leisure, which is not according expectation too. Because one is able to relax in an AV-leisure, it was not expected that the marginal disutility was largest in this mode of transport. According to this conclusion it stood out that in all modes it is preferred to travel alone. It was expected that one prefers to travel alone when travelling in an AV with office interior, since it advances working activities. Unfortunately, a mode-specific travel company parameter for the AV-office and AV-leisure was not significant. Next, it can be concluded that travellers of the AV with office interior prefer substituting travel time for working time instead of working extra time. This finding proves that one prefers staying longer at home rather than in the office. Regarding the value of travel time, it is concluded that a delay in travel time is experienced least worse in an AV with office interior. AV-office users are approximately willing to pay 7.7 eurocents per minute compared to 14.6 eurocents per minute and 15.9 eurocents per minute for users of respectively the conventional car and the AV with leisure interior. The VOTT for car-users estimated with this model approaches VOTTs found in other studies (€9.00 per hour by Kouwenhoven et al. (2014) and €9.30-9.90 by Yap et al. (2016)). At last, users of the AV with leisure interior are willing to pay most money to reduce their travel time. An explanation could be that one rather be, for example, at home or at a bar to have leisure time instead of on the road.

The final MNL model estimated without non-trader data achieved also an improvement in adjusted Rho-Square. The estimation results gave away that no preference is observed for automated driving. In contrast to the above-discussed model, socio-economic variables about age and daily occupation are significant in this case. It can be concluded that the employed population (full- and part-time) prefer driving a car, while retirees have a preference for AVs. Coefficients that explains the behaviour of train and bike users are not significant. Another interesting conclusion is that youngster prefer AVs, while older people have a predilection for driving a car themselves. An explanation for this observation is that older people are more sceptically about computer driven cars. However, it is contradictory since retirees are under normal condition older people. A marginal utility coefficient for the age category 26-60 was not significant. Next, it is concluded that a preference exists for saving time at the office (substitute travel time for working time) rather than working additional time. When looking at the VOTTs it is concluded that users of the AV-office are willing to pay less money (€0.083 per min) related to the users of the other modes (€0.131 per min and €0.175 per min, respectively car and AV-leisure). The value found for AV-office users is entirely according expectation. The value found for AV-leisure users was not according expectation, however a logical reason for the outcome has been provided in the previous indention. At last, the VOTT of car users estimated with this model has a larger discrepancy with other VOTT studies. However, this is not considered as a problem, since this study is an exploratory study.

APPENDIX G: RESULTS AV-CASE NESTED LOGIT MODELS

In this appendix the results of the Nested Logit (NL) models will be discussed. In subsection 3.2.2 it is explained what NL implies and how the model structure is set up. The final estimated MNL models are used as base for the NL models. NL structures are applied when it is expected that alternatives have a high correlation with each other. In this study, it is expected that the two AV alternatives have commonalities, since both options are not yet existing alternatives and both options are computer-driven vehicles. Another reason for testing whether these alternatives belong to the same nest is that the names have identical parts (automated vehicle with red.). The expected nest is tested in the final model estimated with the full sample as well as the final model estimated from the data leaving out the non-traders. However, it is also tested if the conventional car alternative belongs to the same nest as the AV-office alternative, and if the conventional car alternative belongs to the same nest as the AV-leisure alternative.

The estimated NL model (all respondents) is discussed first, then the estimated NL model (excl. non-traders) is discussed. At last, conclusions will be drawn from the outcomes of both estimations.

RESULTS NL MODELS

Table 0.21 shows the statistics of the NL models. In comparison to the finals MNL models one additional parameter is estimated, which is the nest parameter. The statistics of the NL models indicate that one or more significant nest parameter were estimated that improve the explanatory power of the model. The adjusted Rho-Square of the NL model excluding non-traders has not changed compared to the final MNL model. This implies that none of the three estimated nest parameters add value.

Table 0.21: Statistics discrete choice NL model estimations.

	NL with full sample	*NL excl. non-traders*
Number of observations	3,024	2,136
Number of estimated parameters	20	20
Null log-likelihood	-3,322.204	-2,346.636
Final log-likelihood	-2,614.156	-1,964.630
Adjusted Rho-Square	0.212	0.154

The following table shows the results of NL model where the AV-office and the AV-leisure belong to the same nest. The alternatives AV with office interior and AV with leisure interior are nested in the parameter *future*. The *existing* parameter consists the conventional car alternative and is fixed on 1. In both NL models the nest parameter is 1, meaning that the AV-office and AV-leisure does not belong to a nest. The t-test (0) tests the model in comparison to no model. The t-test(1) tests if the NL model differs from the MNL model. If the t-test (1) is significant, then there is a correlation between the unobserved utilities of the nested alternatives. In both models the t-test(1) is not significant, thus the NL model is in both cases not different with respect to the MNL model.

Table 0.22: Nest parameters for AV-office & AV-leisure in the same nest.

Full sample NL	*Value*	*Std. error*	*t-test (0)*	*p-value*	*t-test (1)*	*p-value*
Existing	1.00	-	-	-	-	-
Future	1.00	0.196	5.11	0.00	0.00	1.00
Excl. non-traders NL						
Existing	1.00	-	-	-	-	-
Future	1.00	1.80e+308	0.00	1.00	0.00	1.00

Because there is no correlation between the unobserved utilities of the AV alternatives the MNL models are maintained. The estimated marginal utility coefficients are the same as in the final MNL models, so no tables of estimation results are provided.

Table 0.23 shows the results of the NL model where the conventional car and the AV-office belong to the same nest. The results indicate that this nest is significant. This means that these alternatives have (strong) commonalities according the respondents. This result is only significant in the case the full sample was used for the model estimation. An explanation could be that people are also able to work while driving in a conventional car. One could make phone calls while driving to work. This results was not according expectation, but very interesting.

Table 0.23: Nest parameters for AV-office & conventional car in the same nest.

Full sample NL	*Value*	*Std. error*	*t-test (0)*	*p-value*	*t-test (1)*	*p-value*
AV-leisure	1.00	-	-	-	-	-
AV-office & car	1.63	0.142	11.45	0.00	4.41	0.00
Excl. non-traders NL						
AV-leisure	1.00	-	-	-	-	-
AV-office & car	1.26	0.152	8.29	0.00	1.72	0.09

Table 0.24 shows the results of the NL model in which the AV-leisure alternative and the conventional car alternative belong to the same nest. The estimated results indicate that no significant nest parameter was estimated using either the full sample or the sample excluding non-traders.

Table 0.24: Nest parameters for AV-leisure & conventional car in the same nest.

Full sample NL	*Value*	*Std. error*	*t-test (0)*	*p-value*	*t-test (1)*	*p-value*
AV-office	1.00	-	-	-	-	-
AV-leisure & car	1.00	1.80e+308	0.00	1.00	0.00	1.00
Excl. non-traders NL						
AV-leisure	1.00	-	-	-	-	-
AV-leisure & car	1.00	1.80e+308	0.00	1.00	0.00	1.00

Because the nest parameters in the estimated NL models using data excluding non-traders resulted in a MNL model, the estimation results of the other parameters are not shown. However, the nest parameter is significant in the case the AV-office and the conventional car belong to the same nest. This influence explanatory power of the model and the estimation results compared to the MNL model. Table 0.25 shows the estimation results of the significant NL model.

The marginal valuations of the variables are almost all lower compared to the final MNL model. It is striking that in the NL model the *Activitiy_AV_office* parameter is insignificant.

Table 0.25: Estimation results of the NL model with AV-office & conventional car in nest (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	0.451	0.371	1.22	0.22	0.365
Traveltime_AV_leisure	-0.0372	0.00425	-8.76	0.00	0.00431
Traveltime_AV_office	-0.0214	0.00407	-5.27	0.00	0.00399
Traveltime_car	-0.0275	0.00387	-7.1	0.00	0.00399
Travelcosts_AV_leisure	-0.255	0.0261	-9.79	0.00	0.0266
Travelcosts_AV_office	-0.312	0.0272	-11.49	0.00	0.0271
Travelcosts_car	-0.228	0.0405	-5.64	0.00	0.0393

Activity_AV_office*	-0.0495	0.0408	-1.21	0.23	0.04
Travel_company_AV	-0.116	0.0255	-4.55	0.00	0.0254
Travel_company_car	-0.144	0.0476	-3.02	0.00	0.0467
Walkingtime_car*	0.0182	0.0262	0.69	0.49	0.0269
AbleToWork_car	0.112	0.0379	2.94	0.00	0.0387
WillingToWork_car	0.236	0.0459	5.14	0.00	0.0448
Buy-AV_car	0.27	0.0485	5.58	0.00	0.0477
Convenience_car	-0.534	0.0556	-9.59	0.00	0.0565
Safety_car	-0.204	0.0423	-4.82	0.00	0.0442
Trust_car	0.174	0.0394	4.41	0.00	0.0397
Mode_BMT_car	0.754	0.147	5.12	0.00	0.147
Mode_carpool_car	-1.28	0.19	-6.75	0.00	0.19

** = not significant in a 95% confidence interval.*

The next step is calculating the VOTT of the travellers of all modes using the ratio of the travel time parameter and the travel costs parameter. Table 0.26 shows the estimated mean VOTT from the NL model. Compared to the final MNL model a switch was made in relative ranking. The VOTT of the AV-office users is estimated lowest compared to the other travellers, however the VOTT of the AV-leisure travellers is higher than the VOTT of the conventional car users. This outcome is not in line with the expectation. The mean VOTT estimates of the conventional car user and the AV-office user are lower compared to the mean VOTT estimates of these traveller group of the MNL model. The mean VOTT estimate of the AV-leisure traveller is higher according the NL model than the mean VOTT estimate for AV-leisure travellers according the final MNL model.

Table 0.26: The VOTTs estimated from the NL model with AV-office & conventional car in a nest.

Full sample MNL	*Value*	*Std. error*	*Value*
VOTT Car	0.121 [€/min]	0.0185	7.24 [€/hr]
VOTT AV with office interior	0.069 [€/min]	0.0138	4.12 [€/hr]
VOTT AV with leisure interior	0.146 [€/min]	0.0233	8.75 [€/hr]

Table 0.27 shows the results of Welch's t-test. The t-test showed that the VOTT found for car travellers and for AV-leisure travellers do not differ significantly from each other in the 95% reliability interval.

Table 0.27: Results Welch's t-test of the VOTTs within the estimated NL models.

Full sample MNL	*t-value*	
VOTT Car – VOTT AVO	2.26	Significant
VOTT Car – VOTT AVL	0.85	Not significant
VOTT AVO – VOTT AVL	2.85	Significant

CONCLUSIONS NL MODELS

We can conclude that the expectation was false according the NL models. It appears that not the two AV alternatives belong to the same nest, but that the conventional car alternative and the AV-office alternative belong to the same nest. An explanation why the expectation was false can be found in the descriptive of the alternatives. The descriptive of the AV-office mentioned that the interior of this vehicle is designed to work, so with stable internet connections and other conveniences of an office. While the AV-leisure is explained as an vehicle which enables the user to have on a comfortable way leisure time. It provides means to watch a movie, read a book or have quality time with friends or family. These descriptions could have led that the two AVs are experienced as two different modes of transport.

An explanation why the conventional car and the AV-office belong to the same nest can be provided as well. Currently, it is possible to make phone calls when driving to your work which can be associated with work. In the AV-office one can make calls for working purposes as well. This could result that respondents experience commonalities in these modes of transport.

However, it is striking that no significant nest parameter is observed when estimating NL models using data that exclude non-traders.

APPENDIX H: RESULTS AV-CASE ERROR-COMPONENT MIXED LOGIT WITH PANEL EFFECT MODELS

This appendix is dedicated to the execution of the error-component mixed logit (ML) model and its results. The error-component ML model assumes that the alternative-specific constants (α) are randomly distributed instead of being fixed. The final MNL models are taken as base for estimating the error-component ML models. Within these models the degree of variation in unobserved preference for AV is estimated. If the degree of variation (σ_{α_AV}) is not zero and significant, then unobserved heterogeneity is measured for automated driving. So, to capture the error-component effect the utility functions (Equation 43 and Equation 44) are altered, such that:

Equation 48

$$\alpha_{AV} \sim N(\alpha_{AV}, \sigma_{\alpha_{AV}})$$

Where α_{AV} represents the alternative-specific constant, and σ_{α_AV} the degree of variation. First the estimated error-component ML from the full data is discussed, followed up by the error component ML model estimated from data leaving out the non-traders.

RESULTS ERROR-COMPONENT ML MODELS

Two error-component ML models are estimated from all data. The first model makes use of a normal distribution of the degree of variation, while the other models makes use of the uniform distribution. 1000 Draws are used to estimate the models. Table 0.28 shows the statistics of the estimated error-component ML models. The adjusted Rho-Square has been improved regarding both models. With respect to the full sample it improves from 0.207 in the final MNL model to 0.304 in the error-component ML with panel effect model. When excluding the non-traders the adjusted Rho-square is improved from 0.155 to 0.171.

Table 0.28: Statistics discrete choice error-component ML model estimations.

	Error-comp. full sample	*Error-comp. excl. non-traders*
Number of observations	3,024	2,136
Number of estimated parameters	20	20
Number of individuals	252	178
Null log-likelihood	-3,322.204	-2,346.636
Final log-likelihood	-2,292.593	-1,924.967
Adjusted Rho-Square	0.304	0.171

First the estimation results of the error-component model estimated from the full sample will be discussed. Table 0.29 shows the estimation results of this model. On average no preference is observed for the AV, since the ASC is insignificant. However, the degree of variation in unobserved preference for AVs (sigma) is significant. An significant standard deviation means that there is significant and substantial heterogeneity. So, if one of the AV alternatives is improved it has more effect on the other AV alternative rather than the car alternative.

Furthermore, travel time is valued most negatively in the car (-0.0653), and least negatively in the AV-office (-0.0358). An increase in travel costs with one euro is experienced worst when travelling in the car (-0.485), second worse in the AV-office (-0.468) and least worse in the AV-leisure (-0.303). Still, saving time at the office is preferred over working additional time (-0.181). Travelling accompanied in an AV is not estimated significantly in this model, thus equals 0.00. However, in the normal car it is preferred to travel alone (-0.285). The error-component ML model estimated the waiting time significant, however the parameter is positive. This means that a one-minute increase in walking time increases the overall utility of the car alternative with 0.0897 utile. This results is not according expectation, since walking extra time is normally experienced negatively. The marginal utility value for being able to work in an AV is not significant and therefore equals 0.00. In the case that a respondent is willing to work in an AV (0.468) and/or willing to buy an AV (0.566) an AV alternative has the preference. The marginal utility factors of the latent factors are according expectation. The AV is preferred over the car regarding car-poolers (-2.81), while BMT users prefer the conventional car (1.69). Full time workers prefer the car as well (-1 * -2.81 + -1 * 1.69 = 1.12).

Table 0.29: Estimation results of the error-component ML with panel effect model (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	-0.322	0.69	-0.47	0.64	0.563
Sigma_constant_AV	-2.23	0.174	-12.84	0.00	0.206
Traveltime_AV_leisure	-0.0629	0.00571	-11.02	0.00	0.00679
Traveltime_AV_office	-0.0358	0.00506	-7.07	0.00	0.00467
Traveltime_car	-0.0653	0.00619	-10.54	0.00	0.00691
Travelcosts_AV_leisure	-0.303	0.0302	-10.04	0.00	0.0355
Travelcosts_AV_office	-0.468	0.0331	-14.14	0.00	0.04
Travelcosts_car	-0.485	0.0679	-7.14	0.00	0.0603
Activity_AV_office	-0.181	0.0553	-3.28	0.00	0.0429
Travel_company_AV*	-0.0517	0.0317	-1.63	0.10	0.0299
Travel_company_car	-0.285	0.0747	-3.81	0.00	0.0726
Walkingtime_car	0.0897	0.0393	2.29	0.02	0.0339
AbleToWork_car*	0.261	0.191	1.37	0.17	0.177
WillingToWork_car	0.468	0.222	2.11	0.04	0.198
Buy-AV_car	0.566	0.236	2.4	0.02	0.223
Convenience_car	-1.43	0.239	-5.99	0.00	0.241
Safety_car	-0.6	0.202	-2.97	0.00	0.205
Trust_car	0.467	0.192	2.43	0.02	0.196
Mode_BMT_car	1.69	0.7	2.41	0.02	0.618
Mode_carpool_car	-2.81	0.865	-3.25	0.00	0.795

** = not significant in a 95% confidence interval.*

The results of the estimated model from the data excluding non-trader are shown in Table 0.30. Just as in the MNL model the alternative-specific constant for AV driving is not significant, so no preference for AVs over the conventional car is observed. However, the sigma has been found significant, so there is a variation in unobserved preference for AV. With a sigma value of -0.889 significant heterogeneity is observed. So, if one of the AV alternatives is improved it has more effect on the other AV alternative instead of the car alternative.

Regarding the marginal travel time coefficients the same behaviour as in the MNL model is observed. An increase in travel time is lower in the AV with office interior (-0.043) than in the AV with leisure interior (-0.0699) and the conventional car (-0.0643). This indicates that in-vehicle time travel time valuation when travelling in an AV-office is approximately 40% lower compared to AV-leisure travelling, and about 33% compared to travelling with a normal car. The mode-specific travel cost valuation is most positive in the AV with leisure interior (-0.373). Respondents are more sensitive to travel costs increases in the normal car (-0.493) and the AV-office (-0.523). Working extra time is valued negatively (-0.161) compared to substituting travel time for working time (0.161). Travelling alone has a positive valuation (car: 0.266, AV: 0.0759) with respect to travelling with family/friends in the car alternative and the AV alternatives. The walking time is not significant and therefore equals 0.00. People older than 60 years have a preference for the normal car alternative (0.371). No significant age indicator is estimated for the age category 26-60, thus no preference for one of the alternatives has been observed. Young people (<26 years), have a preference for automated vehicles given the one significant age indicator (-1 * 0.371 = -0.371 regarding car). It is indicated that if one is willing to work in an AV and if one is able to buy an AV the AV alternatives are valued more positively. Furthermore, a positive attitude regarding the conveniences of automated driving results in a negative car valuation (-0.353). Retirees have a negative valuation regarding the car (-0.679), while full-time workers value the car alternative positively (0.679). The marginal utility valuation of part-time workers is not significant anymore and thus equals zero. Car-poolers value the car alternative negatively (-1.64), while BMT travellers gain marginal utility regarding the car alternative (0.981). Current car associate a higher utility to using a car (-1.64 * -1 + -1 * 0.981 = 0.659), and are less willing to use an AV.

Table 0.30: Estimation results of the error-component ML with panel effect model (excl. non-traders).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	0.469	0.674	0.70	0.49	0.567
Sigma_constant_AV	-0.889	0.0937	-9.49	0.00	0.0915
Traveltime_AV_leisure	-0.0699	0.00609	-11.48	0.00	0.00765
Traveltime_AV_office	-0.043	0.00577	-7.46	0.00	0.00594
Traveltime_car	-0.0643	0.0063	-10.22	0.00	0.00695
Travelcosts_AV_leisure	-0.373	0.034	-10.98	0.00	0.0416
Travelcosts_AV_office	-0.523	0.0354	-14.77	0.00	0.0447
Travelcosts_car	-0.493	0.0713	-6.91	0.00	0.0659
Activity_AV_office	-0.161	0.06	-2.69	0.01	0.0487
Travel_company_AV	-0.0759	0.0345	-2.20	0.03	0.035
Travel_company_car	-0.266	0.0772	-3.44	0.00	0.0747
Walkingtime_car*	0.0448	0.0409	1.10	0.27	0.0369
Age1_car	0.371	0.187	1.98	0.05	0.206
WillingToWork_car	0.328	0.106	3.10	0.00	0.101
Buy-AV_car	0.465	0.113	4.11	0.00	0.113
Convenience_car	-0.353	0.138	-2.57	0.01	0.0487
DO_retired_car	-0.679	0.252	-2.70	0.01	0.241
DO_workpt_car*	0.321	0.183	1.76	0.08	0.167
Mode_BMT_car	0.981	0.363	2.71	0.01	0.348
Mode_carpool_car	-1.64	0.463	-3.54	0.00	0.457

** = not significant in a 95% confidence interval.*

Since the adjusted Rho-Squares of the error-component ML with panel effect model are higher than its MNL counterpart new VOTTs are estimated. Table 0.31 shows the estimated VOTTs and the computed standard errors. All the standard errors are acceptable low such that the all the VOTTs are significant in a 95% reliability interval. According to both models, users of the AV with office interior are willing to pay less money (€4.61-4.93 per hour) compared to the car users (€7.83-8.77 per hour) and the AV-leisure users (€9.54-11.24 per hour). The VOTT regarding car users is in line with Kouwenhoven et al. (2014) and Yap et al. (2016).

Table 0.31: The VOTTs estimated from the error-component ML with panel effect models.

Full sample error-comp. ML	*Value*	*Std. error*	*Value*
VOTT Car	0.135 [€/min]	0.015	8.77 [€/hr]
VOTT AV with office interior	0.076 [€/min]	0.012	4.61 [€/hr]
VOTT AV with leisure interior	0.208 [€/min]	0.027	9.54 [€/hr]
Excl. non-traders error-comp. ML			
VOTT Car	0.130 [€/min]	0.0148	7.83 [€/hr]
VOTT AV with office interior	0.082 [€/min]	0.0120	4.93 [€/hr]
VOTT AV with leisure interior	0.187 [€/min]	0.0223	11.24 [€/hr]

Furthermore it is compared whether the ratios found within the same model differ significantly from each other. Table 0.32 shows the outcomes of the t-test. All parameters are significantly different from each other within the 95% reliability interval.

Table 0.32: Results Welch's t-test of the VOTTs within the estimated error-component ML models.

Full sample error-com. ML	*t-value*	*df.*	
VOTT Car – VOTT AVO	3.04	474	Significant
VOTT Car – VOTT AVL	2.38	396	Significant
VOTT AVO – VOTT AVL	4.50	345	Significant
Excl. non-traders error-com. ML			
VOTT Car – VOTT AVO	2.53	339	Significant
VOTT Car – VOTT AVL	2.13	308	Significant
VOTT AVO – VOTT AVL	4.16	272	Significant

The following table provides an overview to check whether the VOTTs found between the estimated models are significant. The outcome of the last Welch's t-test is that all the VOTTs differ significantly from each other.

Table 0.33: Results Welch's t-test of the VOTTs between the error-component ML models.

	t-value	*df.*	
VOTT Car	2.88	385	Significant
VOTT AV with office interior	4.92	377	Significant
VOTT AV with leisure interior	8.53	416	Significant

CONCLUSIONS ERROR-COMPONENT ML MODELS

It can be concluded that an unobserved heterogeneity in preference for the AV alternatives exists. However, there is no mean preference for the use of AVs. It is also concluded that travellers on average associate more disutility to the travel time in an AV-leisure compared to the AV-office. More disutility is associated with travel costs when travelling in the AV with office interior in comparison to the other alternative. As a consequence it is concluded that people travelling with the AV-office are clearly willing to pay less money to reduce their travel time in comparison to car users or the AV with leisure interior users. AV-office users' VOTT is about 37-47% lower than the VOTT of car users. So it can be concluded that the possibility of working in an AV decreases the willingness to pay for reducing the travel time.

Furthermore it is concluded that travelling alone is associated with utility in all modes, while travelling with companions is associated with disutility. Next it is showed that attitudinal factors play an important role in choice behaviour regarding automated driving. Especially a positive attitude regarding the conveniences of automated driving is associate with a positive valuation for AVs.

APPENDIX I: RESULTS AV-CASE MIXED LOGIT WITH PANEL EFFECT MODELS

In this appendix the results of the estimated mixed logit models with panel effects are discussed. Because tastes (βs) could differ across people, a mixed logit with panel effect is used to test if heterogeneity exists across certain parameters. Making use of panel-data, tastes are made individual-specific, so that a part of the correlation between choices made by the same respondent over time are captured. In this case, each individual made twelve choice observations, the ML allows us to capture more realistic substitution patterns, more realistic taste of heterogeneity levels and some of the correlation across choices made by the same individual. ML models with panel effect are estimated with both the data with and without the non-traders. By constructing the ML models with panel effect the final MNL model has been taken as base. In this study the ML models allows to vary randomly in the travel time parameters. ML models tend to be unstable when all parameters are allowed to vary (Ruud, 1996). By holding the costs parameters fixed this problem is solved, and the VOTT is not the ratio of two distributions. A ratio of two normal distributions follows the Cauchy distribution, which is undesirable (Brownstone, 2000). It is chosen to apply only the normal distribution due to time constraints, because one model simulation took around 8-12 hours. Thus the utility functions are modified such that:

Equation 49

$$\beta_{TT\_CAR} \sim N\left(\beta_{TT\_CAR}, \sigma_{\beta_{TT\_CAR}}\right)$$

Equation 50

$$\beta_{TT\_AVO} \sim N\left(\beta_{TT\_AVO}, \sigma_{\beta_{TT\_AVO}}\right)$$

Equation 51

$$\beta_{TT\_AVL} \sim N\left(\beta_{TT\_AVL}, \sigma_{\beta_{TT\_AVL}}\right)$$

Where the β_{TT} is the mode-specific parameter for travel time (mean taste), and the σ_β us the degree of unobserved taste variation for travel time. If all the estimated sigmas are insignificant, then the ML model becomes a MNL model. Then, there is no individual-specific variation in unobserved taste is measured. Next, it appears that no correlation between unobserved utilities driving choices made by the same traveller is measured, and all variation in utilities is nicely captured in a deterministic utility. First the panel-ML model estimated with all data is discussed. Subsequently the estimated model from data excluding non-traders is estimated.

RESULTS ML WITH PANEL EFFECT MODELS

As mentioned before, a normal distribution has been used. For each model 1,000 draws, and 1,000 iterations are used to come up with the estimated model. As can be seen in Table 0.34 the number of estimated parameters is 22 for both models from which 17 (full sample) and 18 (excl. non-traders) are significant. The final log-likelihood is in both cases lower than their equivalent MNL models: -2,614.156 (full sample) and -1,964.630 (excl. non-traders). This is also reflected in the increase of the adjusted Rho-Square, which is 0.207 for the MNL (full sample) and 0.155 (excl. non-traders).

Table 0.34: Statistics discrete choice ML with panel effect model estimations.

	ML with full sample	*ML excl. non-traders*
Number of observations	3,024	2,136
Number of estimated parameters	22	22
Null log-likelihood	-3,322.204	-2,346.636
Final log-likelihood	-2,081.915	-1,857.040
Adjusted Rho-Square	0.367	0.199

So, first the results of the ML model with panel effect estimated from all the data is discussed. The travel time coefficient of the car alternative is much higher than the value found by Yap et al (2016), but it is in line with Arentze & Molin (2013). The travel cost parameter for cars is in this model doubles the value found by Yap et al. (2016). The AV travel time marginal utility value found by Yap et al. (2016) is in line with these estimated values (-0.084).. The AV travel costs parameter (-0.41) by Yap et al. (2016) is on the other hand less negatively than the values found in this model.

Table 0.35 shows the results of the panel-ML model estimated from the full sample. At first it stands out that all the marginally utility parameters are higher in the panel model than in the MNL model. An explanation could be that the panel model eats away from the normalised iid-error. Hence, most of the t-values of non-travel time parameters are increased. Next, it is striking that an increase in travel time is now experienced least worse (-0.0608) when travelling in a normal car, while in the MNL model AV-office users got least disutility from an increase in travel time. Hence, the sigma of the travel time for AV-office users is the smallest. This implies that least heterogeneity is observed in the travel time marginally utility coefficient of AV-office travellers. The ML models estimates considerably larger mean values for the travel time parameters compared to the MNL model. This is explained by the fact that the ML model decomposes the unobserved component of utility and normalises the parameters through the scale factor (Sillano & de Dios Ortuzar, 2005). All standard deviations (sigmas) are significant, which means that there is individual-specific variation in unobserved taste for travel time. An explanation could be that the model links some of the behaviour to the exploratory attributes, since no alternative specific constant is significant (Hess et al., 2010). The mode-specific travel cost parameter for the AV-office is valued highest (-0.636), implying that an increase in travel costs produces the most disutility when travelling in an AV-office. An increase in costs is valued least negatively when travelling with the conventional car. The ranking of observed disutility with respect to the travel costs are similar as the final MNL model. The estimated results of the ML model shows the same behaviour with respect to the working activity in the AV with office interior. Saving time in the office is preferred over working extra time. However, the extent of gain (or loss) in utility (±0.202) is larger than in the MNL model. Travelling alone in the conventional car (-1 * -0.215 = 0.215) as well as in an AV (-1 * -0.107 = 0.107) is preferred over travelling with family/friends, which is observed in the MNL model too. The same preference is observed in the MNL model, however just as in the activity attribute the marginal utility parameters are a bit larger. People who are willing to but an AV if it is for sell for the same price as a normal car have a strong preference for automated vehicles. Applying the effect coding (yes is -1, no is +1), the marginally utility for this group of people is 0.562 in favour of AVs. On the other hand, if people are not willing to buy an AV, a strong preference for the conventional car is observed (0.562). This finding is according expectation and also found in the MNL model. The three latent factors are significant and showing the expected behaviour. If one identifies the conveniences of automated driving the car is not preferred (-1.35). The same counts if a decision maker thinks that driving an AV is more safe than driving in a car. In this case the conventional car is not preferred over an AV (-0.623). At last, in the case on does not trust (the technical ability of) automated driving the car is preferred (0.361). Where in the MNL model two *most commonly used mode* coefficients were significant, only one is significant in this estimated ML model. It is observed that car-poolers have a strong preference for automated driving (-1.80 utility for the car alternative). On the other hand, car drivers have a very strong preference for driving a car themselves (-1 * -1.80 = 1.80). Nu judgements can be given for people that used to travel with the train, bike, BMT or another mode, since the coefficients are not statistically significant, and therefore equals 0.00 for all commonly used modes. The estimation results of the ML model showed no significant marginally utility parameters for *able to work in an AV*, and *willing to work in an AV*, whereby the coefficients equals a value of 0.00. The next indention provides an interpretation of the estimation results of the ML model with panel effect (excl. non-traders).

The travel time coefficient of the car alternative is much higher than the value found by Yap et al (2016), but it is in line with Arentze & Molin (2013). The travel cost parameter for cars is in this model doubles the value found by Yap et al. (2016). The AV travel time marginal utility value found by Yap et al. (2016) is in line with these estimated values (-0.084).. The AV travel costs parameter (-0.41) by Yap et al. (2016) is on the other hand less negatively than the values found in this model.

Table 0.35: Estimation results of the ML model with panel effect (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	1.31	0.725	1.81	0.07	0.669
Traveltime_AV_leisure	-0.10	0.00886	-11.32	0.00	0.01010
Traveltime_AV_office	-0.0736	0.00814	-9.04	0.00	0.00909
Traveltime_car	-0.0608	0.008	-7.6	0.00	0.00790
Sigma_traveltime_AVL	-0.0646	0.00571	-11.31	0.00	0.00702
Sigma_traveltime_AVO	0.0534	0.00551	9.7	0.00	0.00632
Sigma_traveltime_car	0.0661	0.00683	9.67	0.00	0.00727
Travelcosts_AV_leisure	-0.494	0.0397	-12.44	0.00	0.0537
Travelcosts_AV_office	-0.636	0.0411	-15.49	0.00	0.0569
Travelcosts_car	-0.443	0.0729	-6.07	0.00	0.0668
Activity_AV_office	-0.202	0.067	-3.02	0.00	0.0599
Travel_company_AV	-0.107	0.0386	-2.77	0.01	0.0423
Travel_company_car	-0.215	0.0818	-2.63	0.01	0.0838
Walkingtime_car*	0.0363	0.0439	0.83	0.41	0.0426
AbleToWork_car*	0.184	0.152	1.21	0.23	0.174
WillingToWork_car*	0.285	0.179	1.59	0.11	0.20
Buy-AV_car	0.562	0.19	2.97	0.00	0.215
Convenience_car	-1.35	0.191	-7.07	0.00	0.228
Safety_car	-0.623	0.158	-3.95	0.00	0.175
Trust_car	0.361	0.146	2.46	0.01	0.150
Mode_BMT_car*	1.04	0.59	1.75	0.08	0.694
Mode_carpool_car	-1.80	0.724	-2.49	0.01	0.84

** = not significant in a 95% confidence interval.*

The alternative specific constant is not significant (0.07), so this equals 0.00. This means that no preference is observed for AVs over normal cars. The mode-specific travel time coefficient is valued most negatively in the AV-leisure, which is observed in the MNL model and the former ML model as well. The same as in the MNL model, the disutility of travel time is least negatively valued in the AV with office interior. However, a discrepancy is observed with the estimation results of the panel-ML model that includes all respondents. In the former panel-ML model least disutility is experienced in the normal car. A possible explanation is given in the discussion of the previous panel-ML model. All sigmas are significant, so heterogeneity is observed in all mode-specific time parameters. Least heterogeneity is found in the time coefficient of the car (-0.0238). The same level of heterogeneity has been found in the time parameters of the AV (0.033). Regarding travel costs, the mode-specific parameter is valued most negatively for the AV with office interior (-0.594), while it is valued the same for the AV with leisure interior and the car (-0.463). A difference with the final MNL model is that the travel costs are now valued equally for the AV-leisure and the car, while in the MNL model travel costs were least negatively experienced in the AV with leisure interior. The costs parameter of the AV-leisure is estimated more precisely given the standard error (0.0384 vs. 0.0733). The value of the *activity* coefficient is according expectation: working extra time (-0.181) is valued negatively, while substituting travel time for work time is valued positively (0.181). In both modes disutility is experienced when travelling in the company of friends or family: -0.108 (AV) and -0.230 (car). If one is willing to work in an AV a preference for travelling with an AV is observed (0.294). The same preference is found if a respondent is willing to buy an AV instead of a normal car (0.485). No strange behaviour is observed with the latent factor *conveniences of automated driving*. If one admires the conveniences of automated driving an AV is preferred (-0.447 * -1 = 0.447). The daily occupation parameter that was estimated for part-time workers appears not to be significant. This means that the marginal value of using a car for this occupation group equals 0.00. The parameter regarding retirees is significant and values the car alternative negatively (-0.693). Full-time employed people have a preference for the car alternative (0.693). All other utility parameters regarding occupation are insignificant, thus equal to 0.00. Persons who use BMT as most commonly mode prefer car usage (0.838), whereas car-poolers prefer the AV (-1.470). Current car users have a preference for the conventional car (-1.470 * -1 + 0.838 * -1 = 0.632). This result was shown by the final MNL model as well. In the ML model with panel effect the indicator parameter for the age category >60 is not significant, meaning that all age categories equal a marginal utility of 0.00 with respect to the car alternative. So, no meaningful conclusion can be drawn regarding age and mode preference with this model.

The travel time parameter and the travel costs parameter for car users doubles the car values found by Yap et al. (2016). Just as with the previous model, the travel time coefficient is in line with the value found by Arentze & Molin (2013). The travel time parameter of AVs (-0.084) found by Yap et al. (2016) is almost the same as the AV-leisure specific parameter found in this model. The travel costs coefficient for an AV is valued less negatively than the costs parameters for AVs in this model.

Table 0.36: Estimation results of the ML model with panel effect (excl. non-traders).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	1.27	0.704	1.81	0.07	0.625
Traveltime_AV_leisure	-0.0835	0.00729	-11.45	0.00	0.0089
Traveltime_AV_office	-0.0620	0.00722	-8.59	0.00	0.00813
Traveltime_car	-0.0646	0.00685	-9.44	0.00	0.00729
Sigma_traveltime_AVL	-0.0329	0.00365	-9.00	0.00	0.00367
Sigma_traveltime_AVO	0.0327	0.00383	8.53	0.00	0.00383
Sigma_traveltime_car	-0.0238	0.00422	-5.64	0.00	0.00384
Travelcosts_AV_leisure	-0.463	0.0384	-12.07	0.00	0.0499
Travelcosts_AV_office	-0.594	0.0394	-15.09	0.00	0.0523

Travelcosts_car	-0.463	0.0733	-6.32	0.00	0.0695
Activity_AV_office	-0.181	0.0656	-2.75	0.01	0.0572
Travel_company_AV	-0.108	0.0378	-2.86	0.00	0.0407
Travel_company_car	-0.230	0.0801	-2.87	0.00	0.0797
Walkingtime_car*	0.0233	0.0427	0.55	0.59	0.0407
Age1_car*	0.288	0.188	1.53	0.13	0.215
WillingToWork_car	0.294	0.108	2.73	0.01	0.110
Buy-AV_car	0.485	0.114	4.24	0.00	0.121
Convenience_car	-0.447	0.14	-3.19	0.00	0.136
DO_retired_car	-0.693	0.255	-2.71	0.01	0.259
DO_workpt_car*	0.331	0.187	1.77	0.08	0.193
Mode_BMT_car	0.838	0.370	2.27	0.02	0.387
Mode_carpool_car	-1.470	0.474	-3.09	0.00	0.508

** = not significant in a 95% confidence interval.*

The next step is determining the VOTT of the identified users groups. However, the calculation is less straight forwards as the applied with the MNL models. Since the time parameters are not fixed (normal distribution) and the travel costs parameters are fixed, the VOTTs follow a normal distribution as well (Hess et al., 2004). So the mean VOTT per user group is now the ratio of the travel-time mean and the fixed travel costs parameter. The standard deviation (sigma) of the VOTT is determined by the ratio travel-time sigma over the travel costs parameter. The VOTT distribution is then determined by (Hess et al., 2004; Sillano & de Dios Ortuzar, 2005):

Equation 52: VOTT distribution when having a normal distributed travel time parameter and a fixed costs parameter.

$$\left.\begin{array}{c}\beta_{TT} \sim N(\mu_{TT}, \sigma_{TT}) \\ \beta_{TC}\ \text{fixed}\end{array}\right\} \frac{\beta_{TT}}{\beta_{TC}} \sim N\left(\frac{\mu_{TT}}{\beta_{TC}}, \frac{\sigma_{TT}}{\beta_{TC}}\right)$$

Where β_{TT} and β_{TC} represent the travel time and travel costs parameter respectively. The mean travel time value is formulated by μ_{TT}, and the standard deviation of the time distribution by σ_{TT}.

The relative ranking of the mean VOTTs provided by the ML models with panel effect is similar as the relative ranking by the final MNL models. The mean VOTT of car users is in the ML model estimated with all data slightly lower (€8.23) than in the model without non-trading (€8.37). In both models the mean VOTT of the AV-office user is lower than the car user's mean VOTT (€6.94 and €6.26), which confirms again the expectation. This suggest that the non-trading is not resulting in systematic bias in the marginal utility coefficients. The mean VOTT of the AV-leisure users is the highest in both models, meaning that this user group is willing to pay the highest amount of money to reduce the travel time. The Welch's t-test cannot be used to compare the ratios with each other, since the VOTT follows a distribution rather than being fixed.

The mean VOTTs found for car drivers approach the values of Kouwenhoven et al. (2014) and Yap et al. (2016), which are €9.00 per hour and €9.30-9.90 per hour respectively. The car user VOTT found in Arentze & Molin (2013) is much higher (€12.42 - €22.74) than these values.

Table 0.37: VOTT estimates with standard deviation from the ML with panel effect models.

Full sample panel ML	*Value*	*Std. dev*	*Value*	*Std. dev*
VOTT Car	0.137 [€/min]	0.149	8.23 [€/hr]	8.95
VOTT AV-office	0.116 [€/min]	0.084	6.94 [€/hr]	5.04
VOTT AV-leisure	0.202 [€/min]	0.131	12.15 [€/hr]	7.85
Excl. non-traders ML				
VOTT Car	0.140 [€/min]	0.051	8.37 [€/hr]	3.08
VOTT AV-office	0.104 [€/min]	0.055	6.26 [€/hr]	3.30
VOTT AV-leisure	0.180 [€/min]	0.071	10.82 [€/hr]	4.26

The downside of the normal distribution is that this distribution in unbounded, meaning that there is a probability of estimating a positive travel time parameter. This means that an increase in travel time is experienced positively instead of negatively. In theory it is possible, for example that one prefers have a commute trip of one hour in a train so he or she is able to work rather than a commute time of 10 minutes (Redmond & Mokhtarian, 2001). However, in reality this behaviour is generally not observed. So, the higher the probability of estimating a positive travel time parameter, and thus negative VOTT estimate, the less reliable the VOTT distribution is.

Figure 0.2 shows the probability density function of the mode specific time parameters estimated on the full data. It is calculated that the probability of having a positive time parameter for the car is 17.9%, for the AV-office 8.4%, and for the AV-leisure 6.1%. The probability of a non-negative time parameter for the car is very large, which means that the reliability of this value is less high than of the other two VOTT distributions.

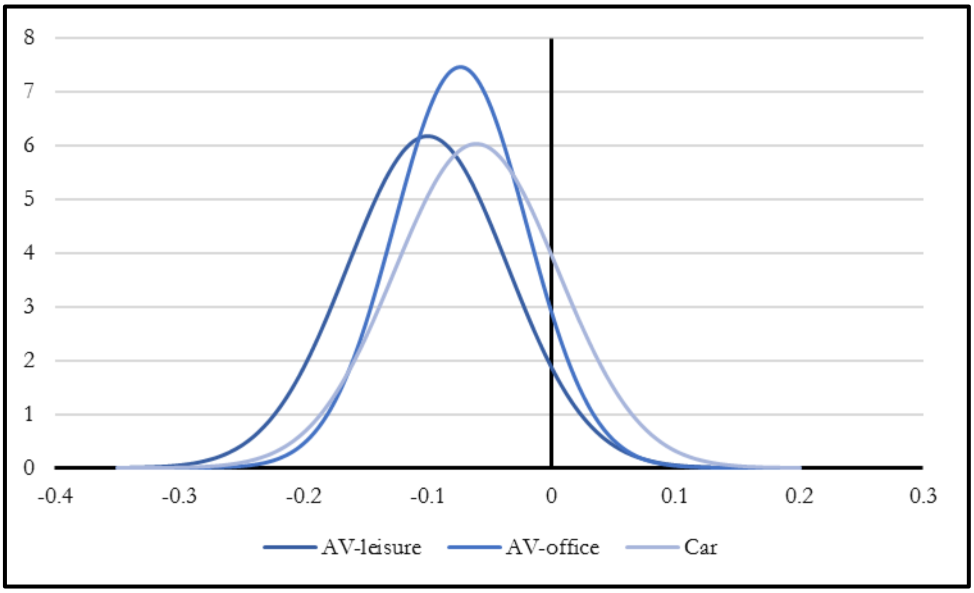

Figure 0.2: Probability density function β_{TT} ML with panel effect model (full sample).

To illustrate the bound of the different distributions, 95% quantile bounds for the VOTTs were calculated. Table 0.38 indicates that the lower 95% quantile limit on all VOTTs have a negative VOTT estimate. So despite the fact that the adjusted Rho-Square is improved making use of the ML logit applying the normal distribution on the mode-specific time parameters there is a risk false conclusions will be drawn.

Table 0.38: 95% quantile intervals for the distribution of the VOTTs (full sample).

	Lower 95% quantile limit	*Upper 95% quantile limit*
β_{TT_CAR}	-9.31 [€/hr]	25.78 [€/hr]
$\beta_{TT\_AV\text{-}OFFICE}$	-2.93 [€/hr]	16.82 [€/hr]
$\beta_{TT\_AV\text{-}LEISURE}$	-3.23 [€/hr]	27.52 [€/hr]

A same illustration of the probability density function of the mode-specific time parameters estimated on the data excluding non-traders has been made. Figure 0.3 provides the probability density functions and indicates that the probability of having a positive mode-specific time parameter is noticeably lower. The probability of obtaining a positive travel time parameter is 0.3% for car, 2.9% for AV-office, and 0.6% fir AV-leisure users.

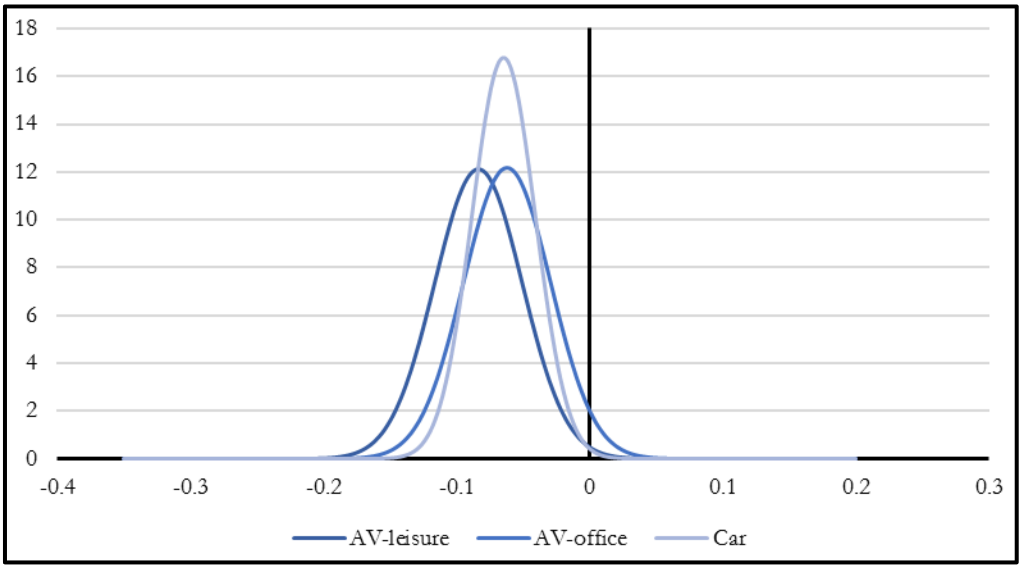

Figure 0.3: Probability density function β_{TT} ML with panel effect model (excl. non-traders).

The 95% quantile bounds are calculated for this matter as well. Table 0.39 provides us the lower and upper 95% quantile limits of the VOTT distributions. It shows that only the VOTT of the users of AV-office users could be estimated negatively in a 95% reliability interval. However, the negative value of €-0.21 per hour is very low, but it can contribute to a false conclusion.

Table 0.39: 95% quantile intervals for the distribution of the VOTTs (excl. non-traders).

	Lower 95% quantile limit	*Upper 95% quantile limit*
β_{TT_CAR}	2.33 [€/hr]	14.42 [€/hr]
$\beta_{TT\_AV\text{-}OFFICE}$	-0.21 [€/hr]	12.74 [€/hr]
$\beta_{TT\_AV\text{-}LEISURE}$	2.46 [€/hr]	19.18 [€/hr]

CONCLUSIONS ML WITH PANEL EFFECT MODELS

The last paragraph of this appendix draws conclusions of the ML with panel effect model. Applying heterogeneity in the time parameters improves the adjusted Rho-Square largely, but it comes with the costs of VOTT estimation reliability.. Less parameters are significant in the ML models, and all but one parameter sign is according expectation.

First, the model results tell us that heterogeneity exists within the travel time, although in the model estimated on the full data more heterogeneity is observed than in the model that excludes non-traders. In fact, the found standard deviations of the model that excludes non-traders are about half the values found in the full-sample model. The average VOTT estimate for AV-office users is lower than the average VOTT estimate of car users and of AV-leisure users according both model results. However, taking the normal distribution of the VOTTs into account it must be said that the reliability of the outcomes produced by the model estimated on data excluding non-traders is much more reliable. High probabilities (6.1% - 17.9%) occur of estimating a negative VOTT estimate for all user groups in the full-sample model, whereas the highest probability of estimating a negative VOTT in the latter model is 2.9%. So despite a big improvement in adjusted Rho-Square, drawing conclusions on normal distributed VOTT estimates is risky, but it provides a nice insight in the heterogeneity of the VOTT for the different travellers.

Furthermore, both models show that travelling alone is preferred over travelling with family/friend no matter the alternative. Regarding the working activity in the AV with office interior, it is concluded that saving time at the office (substitute travel time for time at home) is preferred over working additional time. The results show that car-poolers have a very strong preference for automated driving. Next both models show the importance of the latent attitudinal factor *convenience in automated driving* in the utility of a trip with a car. If one has a positive attitude towards the conveniences of an AV, he or she shows a preference for an AV. Furthermore, the ML model estimated with the full sample shows that the latent factors *safety of automated driving* and *trust in automated driving* are important in the utility of driving a car as well. The ML model estimated without non-trading behaviour explains that retirees prefer AVs, while full-time workers have a preference for the conventional car. No significant differences are found in this model regarding part-time workers. With respect to age no significant differences have been observed.

APPENDIX J: RESULTS AV-CASE COMBINED MIXED LOGIT WITH PANEL EFFECT MODELS

This appendix includes the discussion of the results of the combined ML models. In these models, the ASC parameter is normally distributed as well as the three mode-specific travel time parameters. The mean value and the standard deviation of the four distributions will be estimated by the model. These models aim to check whether heterogeneity exists within the preference indicator and in the taste parameters simultaneously.

RESULTS COMBINED ML WITH PANEL EFFECT MODELS

Table 0.40 shows the statistics of both estimated models. Both models have a lower log-likelihood compared to the taste ML models, which result in higher adjusted Rho-Squares. However, the increase in adjusted Rho-Square in the combined ML model estimated on data excluding non-traders just improved 0.001 compared to the taste ML model (models discussed above). Both the ASC and its standard deviation are not estimated significantly, thus the combined ML model is the same as the taste ML model. An explanation that the model estimated on the sample excluding non-traders estimated insignificant ASC and ASC-sigma parameters, is that the respondents who always choose the same alternative are excluded. This group (non-traders) have a big influence on the ASC, since they prefer constantly the same alternative no matter the variation in attributes. By excluding this (large) group, this preference became apparently insignificant in a 95% reliability interval. For this reason only the combined ML model estimated on the full sample will be discussed.

Table 0.40: Statistics discrete choice combined ML with panel effect model estimations.

	ML with full sample	*ML excl. non-traders*
Number of observations	3,024	2,136
Number of estimated parameters	23	23
Null log-likelihood	-3,322.204	-2,346.636
Final log-likelihood	-2,072.660	-1,854.426
Adjusted Rho-Square	0.369	0.20

Table 0.41 shows the results of the combined ML model estimated on the full sample. Most important findings are that all standard deviations (sigmas) are significant, which means that heterogeneity exists in the preference for AV, and in all three travel time parameters. A longer travel time is valued least negatively in the conventional car (-0.0651) compared to the AV-office (-0.0723) and the AV-leisure (-0.0942). An increase in travel costs by one euro is valued worst by AV-office users (-0.642) with respect to the car (-0.48) and the AV-leisure (-0.488). This models confirms that travelling alone is preferred over traveling with companions, and that one rather saves time at the office while driving in an AV than working extra time. The results indicate further, that if one is not willing to buy an AV he or she prefers the normal car (0.681). All three attitudinal latent factors are significant, which means that they contribute in the decision-making process. A positive attitude regards safety of automated driving and the conveniences of automated driving is valued negatively in a normal car (-0.71 and -1.54 respectively). If one does not trust automated driving a preference for the normal car is indicated (0.433). At last, car-poolers do not prefer the normal car option (-2.27), while full-time workers do (-2.27 * -1 = 2.27).

Table 0.41: Estimation results of the combined ML model with panel effect (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_AV*	1.07	0.759	1.41	0.16	0.695
Sigma_constant_AV	1.61	0.247	6.53	0.00	0.269
Traveltime_AV_leisure	-0.0942	0.00848	-11.11	0.00	0.00969
Traveltime_AV_office	-0.0723	0.00812	-8.9	0.00	0.0097
Traveltime_car	-0.0651	0.00781	-8.33	0.00	0.00806
Sigma_traveltime_AVL	-0.0617	0.00692	-8.92	0.00	0.0112
Sigma_traveltime_AVO	-0.0496	0.00566	-8.77	0.00	0.0065
Sigma_traveltime_car	-0.0525	0.00703	-7.47	0.00	0.00787
Travelcosts_AV_leisure	-0.488	0.0398	-12.25	0.00	0.0543
Travelcosts_AV_office	-0.642	0.0416	-15.44	0.00	0.0585
Travelcosts_car	-0.48	0.0751	-6.39	0.00	0.0698
Activity_AV_office	-0.219	0.0673	-3.25	0.00	0.0603
Travel_company_AV	-0.0966	0.0385	-2.51	0.01	0.0415
Travel_company_car	-0.248	0.0831	-2.98	0.00	0.0867
Walkingtime_car*	0.0438	0.0443	0.99	0.32	0.0435
AbleToWork_car*	0.206	0.197	1.04	0.3	0.232
WillingToWork_car*	0.352	0.245	1.44	0.15	0.298
Buy-AV_car	0.681	0.246	2.77	0.01	0.293
Convenience_car	-1.54	0.266	-5.78	0.00	0.324
Safety_car	-0.71	0.211	-3.37	0.00	0.223
Trust_car	0.433	0.205	2.11	0.03	0.214
Mode_BMT_car*	1.29	0.91	1.42	0.16	1.49
Mode_carpool_car	-2.27	1.08	-2.11	0.03	1.68

** = not significant in a 95% confidence interval.*

With the mean travel time and the sigma of the travel time in combination with the fixed travel costs coefficient, the VOTT distribution can be computed. Because the travel time parameters follow a normal distribution, the VOTT parameters follow this type of distribution as well. The mean VOTT estimate of the AV-office users (€6.76 per hour) is the lowest in comparison with the car travellers (€8.14 per hour) and the AV-leisure travellers (€11.58 per hour). The standard deviation of the AV-leisure users is the largest, which means that most heterogeneity is measured in this group.

Table 0.42: VOTT estimates with standard deviation from the combined ML with panel effect model.

Full sample panel ML	*Value*	*Std. dev*	*Value*	*Std. dev*
VOTT Car	0.136 [€/min]	0.109	8.14 [€/hr]	6.56
VOTT AV-office	0.113 [€/min]	0.077	6.76 [€/hr]	4.64
VOTT AV-leisure	0.193 [€/min]	0.126	11.58 [€/hr]	7.59

As mentioned in the previous appendix, the disadvantage of the normal distribution regarding VOTT estimation is that this distribution is unbounded. So, a probability exists that the travel time parameter is positive, which results in a negative VOTT estimate. The probability density functions of the mode-specific travel time parameters are shown in Figure 0.4. The probability of a positive car travel time estimate is 10.7%. This probability is 7.2% for the AV-office VOTT estimate and

6.3% for the AV-leisure VOTT estimate. The probability of obtaining a positive travel time parameters are lower than in the taste-ML model estimated on the full sample.

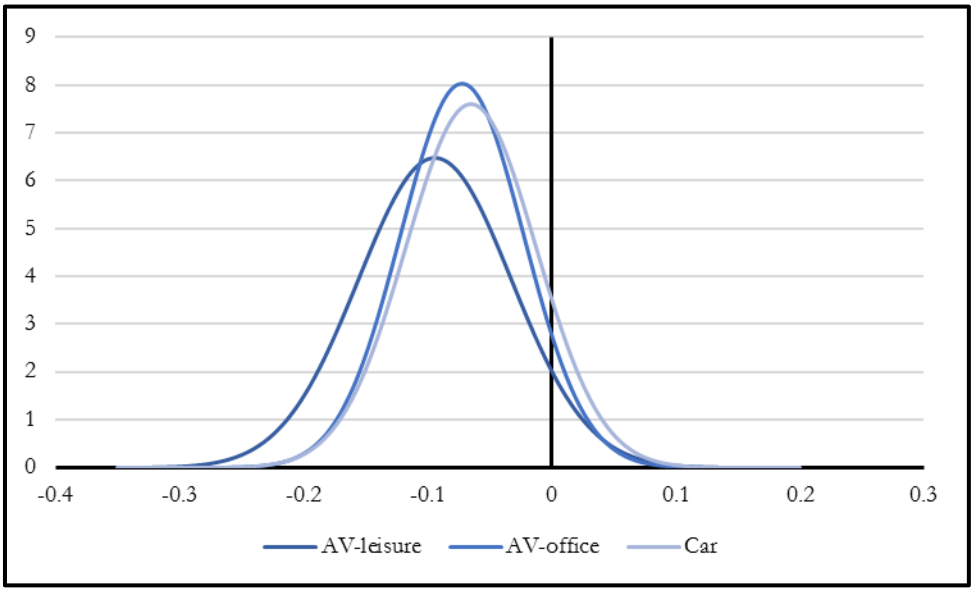

Figure 0.4: Probability density function β_{TT} combined ML with panel effect model (full sample).

The 95% quantile intervals for the VOTT distributions are calculated as well. The results are shown in Table 0.43. It shows that within the 95% quantile it is possible that the model estimates a negative VOTT for an individual.

Table 0.43: 95% quantile intervals for the distribution of the VOTTs (full sample).

	Lower 95% quantile limit	*Upper 95% quantile limit*
β_{TT_CAR}	-4.73 [€/hr]	21.00 [€/hr]
$\beta_{TT\_AV\text{-}OFFICE}$	-2.33 [€/hr]	15.84 [€/hr]
$\beta_{TT\_AV\text{-}LEISURE}$	-3.29 [€/hr]	26.45 [€/hr]

CONCLUSIONS COMBINED ML WITH PANEL EFFECT MODELS

In this sections we discussed the estimation results of the ML models that estimated the ASC and the travel time parameters as normal distributions with a mean and a standard deviation. The model results indicated that the model estimated on the data that excludes non-traders did not fit the data better than the ML model that only estimated the travel time parameters as normal distributions. However, the model estimated on the full sample did significantly improve.

From this model results we can conclude that heterogeneity is observed among the time parameters as well as in the alternative-specific constant. Thus, according this model and dataset variation exists within taste and preference. Next, it may be concluded that the mean VOTT estimate of the AV-office user is considerably lower than the VOTT estimate of the car user and the AV-leisure user. However, a probability exists that a positive time parameter is estimated (thus a negative VOTT estimate), which can be problematic. Still, it provides a good insight in the VOTT of the users of the car, AV-office and the AV-leisure.

APPENDIX K: DESCRIPTIVE STATISTICS CHOICE SETS CHAUFFEUR-CASE

Table 0.44: Descriptive statistics choice sets chauffeur-case.

				Choice set 1
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	193	37	12	242
Share	79.8%	15.3%	5.0%	100%
				Choice set 2
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	119	99	24	242
Share	49.2%	40.9%	9.9%	100%
				Choice set 3
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	175	35	32	242
Share	72.3%	14.5%	13.2%	100%
				Choice set 4
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	154	43	45	242
Share	63.6%	17.8%	18.6%	100%
				Choice set 5
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	99	34	109	242
Share	40.9%	14.0%	45.0%	100%
				Choice set 6
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	120	114	8	242
Share	49.6%	47.1%	3.3%	100%
				Choice set 7
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	128	61	53	242
Share	52.8%	25.2%	21.9%	100%
				Choice set 8
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	103	26	113	242
Share	42.6%	10.7%	46.7%	100%
				Choice set 9
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	101	89	52	242
Share	41.7%	36.8%	21.5%	100%
				Choice set 10
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	163	35	44	242
Share	67.4%	14.5%	18.2%	100%
				Choice set 11
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	172	52	18	242
Share	71.1%	21.5%	7.4%	100%
				Choice set 12
	Conventional car	**AV with office interior**	**AV with leisure interior**	**Total**
Frequency	104	62	76	242
Share	43.0%	25.6%	31.4%	100%

APPENDIX L: ELABORATION OF THE EXPLORATORY FACTOR ANALYSIS

This appendix shows the effectuation of the exploratory factor analysis and the final estimated results of the latent variable model. First the descriptive statistics of all attitudinal statements are shown in the next table.

Table 0.45: Descriptive statistics of the attitudinal variables.

	N	*Min*	*Max*	*Mean*	*Std. error*	*Std. dev.*	*Variance*
ST1	242	1	7	5.7686	0.09649	1.50109	2.253
ST2	242	1	7	4.1736	0.11761	1.82958	3.347
ST3	242	1	7	3.5537	0.11016	1.71375	2.937
ST4	242	1	7	3.314	0.10558	1.64245	2.698
ST5	242	1	7	6.1322	0.08584	1.33539	1.783
ST6	242	1	7	4.1322	0.12626	1.96417	3.858
ST7	242	1	7	4.8678	0.11563	1.79876	3.236
ST8	242	1	7	5.2603	0.10929	1.70013	2.89
ST9	242	1	7	5.0165	0.11638	1.81045	3.278
ST10	242	1	7	5.3347	0.1026	1.59601	2.547
ST11	242	1	7	4.8182	0.11857	1.84458	3.402
ST12	242	1	7	5.3512	0.10051	1.56352	2.445
ST13	242	1	7	5.657	0.0952	1.48091	2.193
ST14	242	1	7	3.6983	0.105	1.63339	2.668
ST15	242	1	7	3.7934	0.12295	1.91269	3.658
ST16	242	1	7	5.9793	0.07996	1.2439	1.547
ST17	242	1	7	5.3967	0.0992	1.54318	2.381
ST18	242	1	7	2.7273	0.12171	1.89343	3.585

For analysing the 18 attitudinal indicators the software package SPSS has been used. For executing the EFA some steps were taken in the factor analysis pop-up, which are explained below.

- In the descriptives wizard: Tick the boxes 'coefficients', 'determinant', and 'KMO and Bartlett's Test of sphericity';
- In the extraction wizard: Pick the 'principal axis factoring' as method, next extract based on an Eigenvalue larger than 1, and display the rotated factor solution and scree plot;
- In the rotation wizard: Choose the varimax method for an orthogonal rotation, and;
- In the options wizard: Choose the exclude missing values listwise.

After the setup of the EFA, several iterations are executed before satisfying results were found. However, prior to the iterations some statistical tests must be conducted. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity are used to assess whether the obtained data is suitable for a factor analysis (Bartlett, 1950; Dziuban & Shirkey, 1974). Especially if the ratio respondents-variables is less than 1:5, the KMO is recommended. If the KMO index is greater than 0.5 it is considered suitable for factor analysis. Besides, the Bartlett's test of sphericity must be significant ($p < 0.05$) as well. (B. Williams et al., 2010).

Table 0.46 shows the outcomes of the KMO measure of sampling adequacy and the Bartlett's test of sphericity. Both tests proof (KMO > 0.5 and Bartlett's test sig. $p < 0.05$) that the dataset is suitable for the factor analysis.

Table 0.46: Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericity.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.842
Bartlett's Test of Sphericity	Approx. Chi-square	1,528
	Degrees of freedom	55
	Significance	0.00

I. The first step after the starting iteration is to check whether indicators have a communality lower than 0.25. In the extraction column attitudinal indicator 1 has a communality of 0.199, so this indicator is eliminated and a second factor analysis has been executed.
II. In the second iteration indicator 5 has a communality lower than 0.25. With a value of 0.219 this indicator is eliminated and a new iteration has been executed.
III. After the third iteration indicator 18 has a factor loading under 0.5. This indicator, with a loading of -0.372, is excluded. A new factor analysis has been conducted.
IV. In the fourth iteration all indicators have a communality above 0.25. Now a three-factor solution was given with several indicators having a factor loading lower than 0.50. It is chosen to exclude indicator 16, since it had the lowest factor loading (0.446).
V. The fifth iteration gives a three-factor solution as well. All attitudinal factors have a communality score higher than 0.25 and all factors have a factor loading higher than 0.50. However, some factors have higher loadings on multiple factors. It is chosen to exclude indicator 6, since it has the lowest communality of the factors that have multiple higher factor loadings.
VI. Iteration number six gives a two-factor solution. However, the scree criterion shows that a three-factor solution is still acceptable despite the Eigenvalue lower than 1.
VII. Iteration number seven, with a forced three-factor solution, shows that indicator 14 loads below 0.5. It loads -0.313, 0.363 and 0.450 on the three factors. After excluding this indicator a new iteration has been done.
VIII. Iteration eight shows that indicator 2 loads just above the border of 0.5 on a factor (0.583). Besides, it has a loading of 0.487 on another factor, so this indicator is excluded as well.
IX. The ninth iteration gives a three-factor solution with all indicators having a communality and factor loading respectively greater than 0.25 and 0.50. The indicators that have multiple loadings on factors score high on one factor and low (close to 0.30) on other factor(s).

The cumulative percentage of the variance of the initial Eigenvalues is 72.98%, of the extraction sums of squared loadings 64.33%, and of the rotation sums of squared loadings 64.33% as well. The Eigenvalue of the third factor is in the rotation sums of squared loading higher than one (1.592). Thee scree plot shows that a three-factor solution is acceptable.

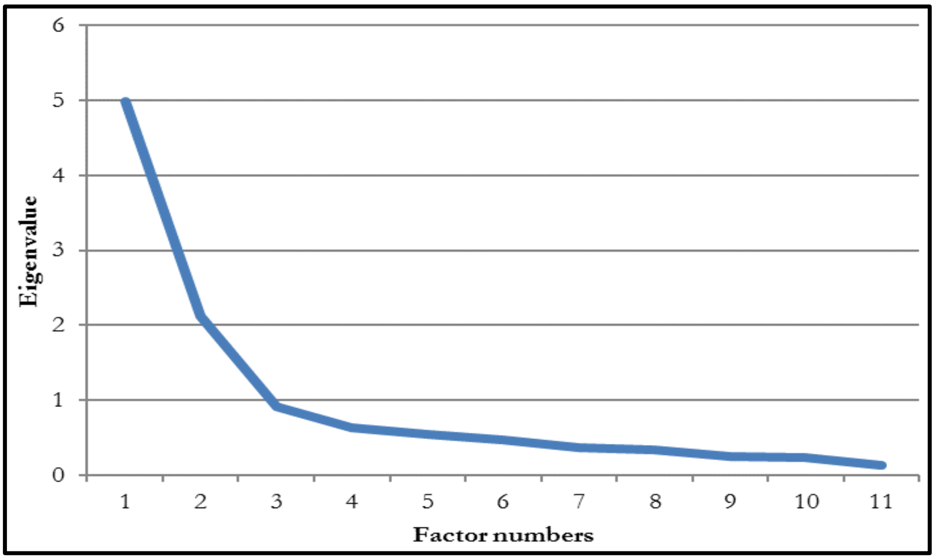

Figure 0.5:Scree plot of the exploratory factor analysis (chauffeur-case).

The last table of this appendix gives the results of the final communalities of the variables.

Table 0.47: Communalities final iteration latent variable model.

	Initial	*Extraction*
ST3	0.748	0.849
ST4	0.758	0.851
ST7	0.564	0.603
ST8	0.525	0.614
ST9	0.525	0.618
ST10	0.453	0.457
ST11	0.679	0.754
ST12	0.651	0.758
ST13	0.572	0.603
ST14	0.527	0.501
ST17	0.405	0.468

APPENDIX M: RESULTS CHAUFFEUR-CASE MNL MODELS

This appendix consists the results of the multinomial logit (MNL) models estimated with the chauffeur-case data. The two datasets include the same information regarding socio-economic variables. Besides it appears that the latent factors identified with the chauffeur-case are almost similar to the latent factors estimated with the AV-case data. The chauffeur-case applies the same effect coding for attribute levels of nominal variables, see Table 0.8.

This case makes also a distinction between the full sample and the dataset excluding non-traders. First two base MNL are estimated, which only includes the SP attributes. Then, after discussing the results of these base MNL models, more elaborated MNL models are estimated. These elaborated models include latent factors and socio-economic variables. The software package that is used for estimating the MNL models is BIOGEME (Bierlaire, 2003).

UTILITY FUNCTIONS

In the MNL models estimated from the chauffeur-case data the same utility function structures are applied. The next equations are similar to the equations shown for the MNL models (AV-case), however some parameters have another name.

Equation 53

$$V_{CAR} = \alpha_{CAR} + \beta_{TT\_CAR} \cdot TT_{CAR} + \beta_{TC\_CAR} \cdot TC_{CAR} + \beta_{WT\_CAR} \cdot WT_{CAR} + \beta_{CO\_CAR} \cdot CO_{CAR}$$

Equation 54

$$V_{CHO} = \alpha_{CH} + \beta_{TT\_CHO} \cdot TT_{CHO} + \beta_{TC\_CHO} \cdot TC_{CHO} + \beta_{AC\_CHO} \cdot AC_{CHO} + \beta_{CO\_CH} \cdot CO_{CHO}$$

Equation 55

$$V_{CHL} = \alpha_{CH} + \beta_{TT\_CHL} \cdot TT_{CHL} + \beta_{TC\_CHL} \cdot TC_{CHL} + \beta_{CO\_CH} \cdot CO_{CHL}$$

Where the α represents the alternative specific constant, and *CAR*, *CHO* and *CHL* are abbreviations of conventional car, car with chauffeur with office interior and car with chauffeur with leisure interior. Also in this case the α of the conventional car alternative is fixed on zero. The parameters β_{TT}, β_{TC} and β_{CO} represent the alternative specific marginal utility parameters for travel time, travel costs and travel company respectively. The parameter β_{WT_CAR} is the marginal utility of the walking time for the conventional car alternative, and at last β_{AC_CHO} gives the marginal utility for the activity attribute in the chauffeur driven office car.

Just as in the comprehensive MNL models of the AV-case the socio-economic variables and the latent factors are only added in the utility function of the conventional car. The utility function of the conventional car has been altered in the same way:

Equation 56

$$\begin{aligned} V_{CAR} = {} & \alpha_{CAR} + \beta_{TT\_CAR} \cdot TT_{CAR} + \beta_{TC_{CAR}} \cdot TC_{CAR} + \beta_{WT_{CAR}} \cdot WT_{CAR} + \beta_{CO} \cdot CO_{CAR} \\ & + \beta_{ABLE} \cdot IV1_{ABLE} + \beta_{WIL} \cdot IV1_{WIL} + \beta_{BUY} \cdot IV1_{BUY} + \beta_{OWN} \cdot IV1_{OWN} \\ & + \beta_{GENDER} \cdot IV1_{GENDER} + \beta_{AGE1} \cdot IV1_{AGE} + \beta_{AGE2} \cdot IV2_{AGE} + \beta_{OC1} \cdot IV1_{OC} \\ & + \beta_{OC2} \cdot IV2_{OC} + \beta_{OC3} \cdot IV3_{OC} + \beta_{OC4} \cdot IV4_{OC} + \beta_{MODE1} \cdot IV1_{MODE} \\ & + \beta_{MODE2} \cdot IV2_{MODE} + \beta_{MODE3} \cdot IV3_{MODE} + \beta_{MODE4} \cdot IV4_{MODE} + \beta_{MODE5} \\ & \cdot IV5_{MODE} + \beta_{CONV} \cdot CONV + \beta_{TRUST} \cdot TRUST + \beta_{SAFETY} \cdot SAFETY \end{aligned}$$

The first five components are the marginal utilities of the SP attributes and the alternative specific constant, which is fixed on zero for the conventional car. Then, β_{ABLE}, β_{WIL}, β_{BUY}, β_{OWN} and β_{GENDER} represent the marginal utility parameters for respectively if one is able to work in an AV, if one is willing to work in an AV, if one is willing to buy an AV for the same price as a conventional car, if one owns a car, and gender. The parameters β_{AGEx}, β_{OCx} and β_{MODEx} are the marginal utility of the nominal variables age, daily occupation and commonly used transport mode. The latter three components of the utility function represents the marginal utility of the identified latent factors: *conveniences of automated driving*, *(dis)trust in automated driving*, and the *safety of automated driving*.

RESULTS BASE MNL MODELS

The statistics of both base MNL models are shown in Table 0.48. The full sample contains 2,903 observations, while the dataset excluding non-traders contains 1,752 observations. The MNL model estimated from the full sample has 9 significant parameters. The MNL model from the data excluding non-traders estimated 10 significant parameters. The adjusted Rho-Square of both models is >0.10, which means that it already predicts reasonably well (see McFadden's Rho-Square, Table 3.1). MNL models with an alternative specific constant for both chauffeur-driven cars were estimated, but the values were not found significant.

Table 0.48: Statistics discrete choice MNL model estimation with only SP attributes.

	MNL with full sample	*MNL excl. non-traders*
Number of observations	2,904	1,752
Number of estimated parameters	11	11
Null log-likelihood	-3,189.271	-1,924.769
Final log-likelihood	-2,639.20	-1,591.194
Adjusted Rho-Square	0.169	0.168

Table 0.49 gives an overview of the estimation results of the base MNL model estimated from the full sample. It is observed that a preference exists for the chauffeur-driven cars given the value of the ASC for chauffeur-driven cars (1.09). An increase in travel time is valued most negative in the leisure-chauffeur car (-0.033) and least negative in the normal car (-0.020). Regarding travel costs, most disutility is experienced when travelling in the chauffeur-driven leisure car (-0.426), however the marginal utility value of the chauffeur-driven office car is almost the same (-0.424). n increase in travel time has been valued much less negative for the normal car. Travelling alone is preferred over travelling with others (-0.152 and -0.242 for travelling with family/friends). The waiting time parameter was not significant and equals 0.00, meaning that given this model it is not influencing the behaviour of the decision-makers. At last, the activity parameter was not significant as well, working additional time or saving time at the office equal a marginal utility of 0.00.

Table 0.49: Estimation results of discrete choice MNL model only with SP attributes (full sample) (CH = chauffeur-driven car).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_chauffeur	1.09	0.487	2.24	0.03	0.48
Traveltime_CH_leisure	-0.0331	0.00499	-6.64	0.00	0.0043
Traveltime_CH_office	-0.0246	0.00545	-4.51	0.00	0.00504
Traveltime_car	-0.0203	0.00443	-4.57	0.00	0.00524
Travelcosts_CH_leisure	-0.426	0.0357	-11.92	0.00	0.0363
Travelcosts_CH_office	-0.424	0.0313	-13.57	0.00	0.0306
Travelcosts_car	-0.129	0.0479	-2.7	0.01	0.0474

Activity_CH_office*	-0.0977	0.0527	-1.85	0.06	0.0518
Travel_company_CH	-0.152	0.0584	-2.61	0.01	0.0572
Travel_company_car	-0.242	0.0357	-6.79	0.00	0.0357
Waitingtime_car*	0.0314	0.0327	0.096	0.34	0.0319

** = not significant in a 95% confidence interval*

Table 0.50 shows the estimation results of the base MNL model from data excluding non-traders. Excluding non-traders mostly influence the alternative-specific constants (Hess et al., 2010). So as expected excluding non-traders affects the ASC of chauffeur-driven cars. In this model a strong preference for chauffeur-driven cars (1.44) is observed as well. An increase in travel time is experienced worst in the chauffeur-driven leisure car (-0.063) and is experienced least negative in the chauffeur-driven office car (-0.0433). This outcome is not in line with the previous model. Travel costs coefficient is valued most negatively for the chauffeur-driven office car (-0.619), followed by the chauffeur-driven leisure car (-0.536) and the normal car (-0.358). The preference for travelling alone in both modes is observed as well (car: -0.247, CH: -0.202 for travelling with companions). Regarding work in the chauffeur-driven office car a preference is observed for substituting travel time for work time, because working extra time is valued -0.18.

Table 0.50: Estimation results of discrete choice MNL model only with SP attributes (excl. non-traders).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_chauffeur	1.44	0.684	2.11	0.03	0.679
Traveltime_CH_leisure	-0.063	0.00654	-9.63	0.00	0.00649
Traveltime_CH_office	-0.0433	0.0069	-6.27	0.00	0.00683
Traveltime_car	-0.0498	0.00629	-7.91	0.00	0.00643
Travelcosts_CH_leisure	-0.536	0.0418	-12.82	0.00	0.0424
Travelcosts_CH_office	-0.619	0.0385	-16.09	0.00	0.0378
Travelcosts_car	-0.358	0.0721	-4.96	0.00	0.0724
Activity_CH_office	-0.18	0.067	-2.68	0.01	0.0662
Travel_company_CH	-0.202	0.0415	-4.88	0.00	0.041
Travel company_car	-0.247	0.0804	-3.08	0.00	0.0777
Waitingtime_car*	0.041	0.0439	0.91	0.36	0.0446

** = not significant in a 95% confidence interval*

The travel costs (-0.20) and travel time (-0.031) parameters found by Yap et al. (2016) is between the values found in this model. The travel time parameter is more in line with Arentze & Molin (2013), since their observed value is between -0.036 and -0.079.

It seems that in this case having travel companions is experienced negatively over travelling alone. To check whether the mode-specific travel company coefficients differ significantly of each other Welch's t-test is used (Welch, 1938). An explanation of the equation is given in 0.

In both base MNL models the mode-specific company coefficients differ significantly from each other. The t-value of the full-sample model is 20.45 and it has approximately 399 degrees of freedom. The t-value is in the excluding non-traders dataset lower, namely 6.05. With 220 degrees of freedom the difference is still significant. So, there is a difference in travelling experience per mode regarding travelling alone or with companions.

The main focus of this study is about trip appreciation, and a tool to measure this is the VOTT. To calculate the VOTT the ratio of travel time and travel costs per alternative has been used. By measuring the VOTT in this manner, the assumption has been made that the coefficients of travel time and travel costs are linear. The Delta method (Daly et al., 2012) is used to calculate the standard errors of the ratios. Table 0.51 shows an overview of the estimated VOTTs.

Table 0.51: The VOTTs estimated from the MNL models only with SP attributes.

Full sample MNL	*Value*	*Std. error*	*Value*
VOTT Car	0.157 [€/min]	0.0476	9.44 [€/hr]
VOTT CH with office interior	0.058 [€/min]	0.0137	3.48 [€/hr]
VOTT CH with leisure interior	0.078 [€/min]	0.0139	4.66 [€/hr]
Excl. non-traders MNL			
VOTT Car	0.139 [€/min]	0.0218	8.35 [€/hr]
VOTT CH with office interior	0.070 [€/min]	0.0118	4.20 [€/hr]
VOTT CH with leisure interior	0.118 [€/min]	0.0151	7.05 [€/hr]

The standard errors of all VOTTs are acceptable small. Only the standard error of car users from the full sample is higher than the standard error of the VOTT of car users found in the model estimated without non-trader data. Both models estimate that the VOTT of the users of the chauffeur-driven car with office interior is lower than the car user's VOTT. This finding is according expectation. The VOTT of the chauffeur-drive leisure car users is in both models between the other values. The VOTT of this category users is much higher (+ €2.39) in the non-traders model. The VOTTs found for car drivers approach the values of Kouwenhoven et al. (2014) and Yap et al. (2016), which are €9.00 per hour and €9.30-9.90 per hour respectively.

Welch's t-test is applied to determine whether the VOTTs statistically differ from each other. The results, shown in Table 0.52, some estimated VOTTs do not differ significantly from each other. The model estimated on data excluding non-traders shows only an insignificant difference between the VOTT of car users and of the chauffeur-driven leisure car users. Only the VOTT estimates of the car users and the chauffeur-driven office car users are significantly different.

Table 0.52: Results Welch's t-test of the VOTTs within the estimated MNL models only with SP attributes.

Full sample MNL	*t-value*	*df.*	
VOTT Car – VOTT CHO	2.00	281	Significant
VOTT Car – VOTT CHL	1.61	282	Not significant
VOTT CHO – VOTT CHL	1.01	482	Not significant
Excl. non-traders MNL			
VOTT Car – VOTT CHO	2.79	223	Significant
VOTT Car – VOTT CHL	0.81	258	Not significant
VOTT CHO – VOTT CHL	2.48	247	Significant

However, the last question that has to be answered is whether the VOTTs found in the different models are significantly different from each other. Welch's t-test is used again. Table 0.53 provides an overview of Welch's t-test results. All found ratios differ significantly from each other.

Table 0.53: Results Welch's t-test of the VOTTs between the estimated MNL models only with SP attributes.

	t-value	*df.*	
VOTT Car	5.14	364	Significant
VOTT CH with office interior	9.06	341	Significant
VOTT CH with leisure interior	25.89	287	Significant

CONCLUSIONS BASE MNL MODELS

In this subsection conclusions are drawn from the base MNL models. Both models have a proper goodness of fit with adjusted Rho-Squares higher than 0.15. So, based on the estimates some conclusions can be drawn. Altogether it can be concluded that a chauffeur-driven car is preferred with respect to the manually driven car. According both MNL models it is concluded that travelling alone is preferred over travelling with family/friends no matter the mode of transportation.

Subsequently, it is observed that the VOTTs of the users of all modes of transport differ significantly from each other. Both base MNL models prove that the VOTT of users of chauffeur-driven cars is lower than the VOTT of individuals driving a car themselves. With these results it can be concluded that people travelling with the chauffeur-driven car with office interior are willing to pay least money to reduce their travel time.

In both models the waiting time was not significant and equals a marginal value of 0.00. So, in this case the waiting time does not influence the (dis)utility of travelling by car. At last, it can be said that saving time at the office is preferred over working extra time in the chauffeur-driven office car. However, only the model that excludes non-traders confirm this statement.

RESULTS EXTENDED MNL MODELS

The base MNL models are expanded with socio-economic variables and with the latent factors, which were identified from 18 indicator variables. First all socio-economic variables and latent factors are used as estimating parameter in the comprehensive MNL model. Then, a new model is estimated with only the significant coefficients

Table 0.54 gives an overview of the statistics of the final MNL models. At the end, the final MNL model based on the full sample estimated 21 parameters from which 18 were significant. The final MNL model estimated from the data excluding non-traders 15 parameters were estimated from which 13 parameters were significant. Both models achieve an improvement in fitness. The adjusted Rho-Square of the final model estimated from the full sample is 0.289 (was 0.169), and the adjusted Rho-Square of the final MNL model excluding non-traders is 0.182 (was 0.168).

Table 0.54: Statistics final discrete choice MNL models.

	MNL with full sample	*MNL excl. non-traders*
Number of observations	2,904	1,752
Number of estimated parameters	21	15
Null log-likelihood	-3,190.370	-1,924.769
Final log-likelihood	-2,248.704	-1,559.707
Adjusted Rho-Square	0.289	0.182

First the estimation results from the final MNL model from all data is discussed, followed up by the other MNL model. First all known socio-economic variables and latent factors were included in the model. It appears that the alternative-specific constant did not significantly differ from zero in the final MNL model estimated from the full sample. Other variables were observed not significant as well. These variables are *walking time car*, *age category >60*, *if one is willing to buy an AV*, *commonly used mode bike*, *commonly used mode car-pooling*, *commonly used mode train*, *daily occupation retired*, *daily occupation student*, *daily occupation working part-time*, and the latent factor *(dis)trust in automated driving.* Because all these variables equal a marginal value of 0.00, the non-SP variables were excluded from the final MNL model. The estimation results of the final MNL model (full sample) are presented in Table 0.55.

As mentioned above, no preference for a chauffeur-driven car is observed. Also the waiting time does not add significant (dis)utility to the car alternative. An increase in travel time of one minute is experienced most negatively in the chauffeur-driven car with leisure interior (-0.0439) and least negatively in the chauffeur-driven office car (-0.029). However, the mode-specific travel time parameter of the normal car is valued almost the same as the chauffeur-driven car with office interior (-0.0295). The marginal utility value of travel costs is lowest for normal car users (-0.201). The increment in travel costs by one euro in the chauffeur-driven car with office interior (-0.475) is almost equally valued as in the chauffeur-driven car with leisure interior (-0.446). The *activity* coefficient is significant and equals -0.132. This means that a saving time at the office is preferred over working additional time. In all modes it is not preferred to travel with family/friends (car: -0.193, CH: -0.211). If a decision-maker is not able to work in a comfortable car, he or she has a preference for the normal car (0.226). The same behaviour is observed if one is not willing to work in an automated vehicle (0.565). In the case a decision-maker owns a car he or she prefers the normal car alternative, since 'yes' is effect coded -1 (-1 * -0.432 = 0.432). The marginal utility coefficient for the age category >60 years has not been found significant and thus equals 0.00. However, respondents in the age category 26-60 have a preference for the chauffeur-driven car. The age parameters are only included in the utility function of the car alternative. Since this parameter equals a negative value (-0.268), people in this age category do not prefer this alternative. However, a preference for the normal car is observed for the respondents in the age category <26 (-1 * -0.268 = 0.268). Regarding gender, males prefer driving a car themselves (0.196), while females prefer a chauffeur-driven car (-0.196). No strange behaviour is observed regarding the two significant latent factors. If one thinks that a trip in an AV is more safe than in a normal car one prefers the chauffeur-driven car. The same behaviour is observed when someone acknowledges the conveniences of an AV. Having trust automated vehicles was not found significant, thus equals a marginal utility of zero. Furthermore, full-time workers have a preference for the chauffeur driven car (scores -0.248 on normal car), while people with the daily occupation 'other' (e.g. jobless) prefer the normal car alternative (0.248). No significant coefficients were estimated for part-time workers, students and retirees. So their marginal utility value regarding the car alternative equals 0.00. The respondents that use bus/tram/metro as most commonly mode do not prefer the conventional car alternative (-0.659). However, respondents that travel usually with a mode other than car, car-pool, bike, BMT or tram (e.g. walk) have a strong preference for the car alternative (0.954). At last, a preference for the chauffeur-driven cars is observed for the car users (-0.659 * -1 + 0.954 * -1 = -0.295). No significant marginal utility coefficients were found for car-poolers, bike users and train travellers, thus these coefficients equal zero.

Table 0.55: Estimation results of final discrete choice MNL model (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_CH*	0.77	0.563	1.37	0.17	0.554
Traveltime_CH_leisure	-0.0439	0.00556	-7.90	0.00	0.00569
Traveltime_CH_office	-0.029	0.00576	-5.03	0.00	0.00555
Traveltime_car	-0.0295	0.00505	-5.85	0.00	0.00503
Travelcosts_CH_leisure	-0.446	0.0369	-12.09	0.00	0.0376
Travelcosts_CH_office	-0.475	0.0332	-14.28	0.00	0.0322
Travelcosts_car	-0.201	0.0541	-3.70	0.00	0.0542
Activity_CH_office	-0.132	0.0563	-2.34	0.02	0.0554
Travel_company_CH	-0.211	0.0365	-5.78	0.00	0.036
Travel_company_car	-0.193	0.0659	-2.93	0.00	0.065
Walkingtime_car*	0.0552	0.0367	1.50	0.13	0.0367
AbleToWork_car	0.226	0.0536	4.22	0.00	0.054
WillingToWork_car	0.565	0.053	10.66	0.00	0.0518
CarOwnership_car	-0.432	0.133	-3.26	0.00	0.12

Age2_car	-0.268	0.101	-2.65	0.01	0.104
Gender_car	0.196	0.05	3.91	0.00	0.0506
Convenience_car	-0.783	0.0609	-12.87	0.00	0.0574
Safety_car	-0.35	0.0541	-6.46	0.00	0.0562
DO_other_car	0.248	0.0826	3.00	0.00	0.0799
Mode_BMT_car	-0.659	0.202	-3.26	0.00	0.227
Mode_none_car	0.954	0.226	4.21	0.00	0.259

** = not significant in a 95% confidence interval*

After discussing the outcomes of the final MNL model estimated from all data, the results of the estimated final MNL model estimated from the data excluding the non-traders are discussed. First all socio-economic variables and latent factors were included in the MNL model. It appeared that multiple parameters were not significant on a 95% reliability interval. These variables were *able to work in an AV*, both *age indicators*, *willing to buy an AV*, *gender*, all *commonly used mode indicators*, *walking time* for car alternative, *all daily occupation parameters,* and the latent factor *(dis)trust in automated driving*. All the insignificant non-SP attributes are left out the final MNL model, where Table 0.56 shows the estimation results of the final MNL model (excl. non-traders).

The respondents have an observed preference regarding chauffeur-driven cars (1.51). Again a one-minute increase in travel time is experienced most negatively in the chauffeur-driven car with leisure interior (-0.0654). An increase in travel time is least worse experienced in the chauffeur-driven office car (-0.0443) and a one-minute increase in travel time in the car is valued between the two chauffeur-driven cars (-0.0521). In the case the travel costs increase with one euro, it is valued most negatively in the chauffeur-driven office car (-0.63), then in the chauffeur-driven leisure car (-0.541) and it is valued less negatively when driving in a normal car (-0.376). Saving time at the office is preferred over working additional time (-0.188). Again, respondents prefer to travel alone no matter what mode travelling with (car: -0.257, CH: -0.196). As mentioned before, the waiting time coefficient is not significant and equals zero. If someone is willing to work in an AV, he or she has a preference for the chauffeur-driven car (-1 * 0.273 = -0.273 for the car alternative). The car ownership variable is in the final MNL model not significant anymore, where it was significant in the MNL model including all socio-economic variables and latent factors. However, since it is not significant the marginal utility value equals now 0.00. At last, the two significant latent factors show logical results. If one thinks that travelling in an AV is safer than a normal car, the car alternative is valued negatively (-0.185), the same counts if respondents acknowledge the conveniences of automated driving (-0.302).

Table 0.56: Estimation results of final discrete choice MNL model (excl. non-traders).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_CH	1.51	0.708	2.13	0.03	0.704
Traveltime_CH_leisure	-0.0654	0.00666	-9.82	0.00	0.00664
Traveltime_CH_office	-0.0443	0.00696	-6.36	0.00	0.0069
Traveltime_car	-0.0521	0.00643	-8.1	0.00	0.00662
Travelcosts_CH_leisure	-0.541	0.0421	-12.83	0.00	0.0428
Travelcosts_CH_office	-0.63	0.0389	-16.19	0.00	0.0381
Travelcosts_car	-0.376	0.0733	-5.12	0.00	0.074
Activity_CH_office	-0.188	0.0675	-2.78	0.01	0.0665

Travel_company_CH	-0.196	0.0416	-4.72	0.00	0.0409
Travel_company_car	-0.257	0.0816	-3.15	0.00	0.0789
Walkingtime_car*	0.0453	0.0446	1.02	0.31	0.0455
WillingToWork_car	0.273	0.0615	4.44	0.00	0.0597
CarOwnership_car*	-0.294	0.152	-1.93	0.05	0.146
Convenience_car	-0.302	0.084	-3.59	0.00	0.0841
Safety_car	-0.185	0.0658	-2.8	0.01	0.0634

** = not significant in a 95% confidence interval*

The next step is computing the corresponding VOTTs with each user group. To compute the VOTT it is assumed that the mode-specific time coefficient as well as the mode-specific costs coefficient are linear. The VOTT is computed by the ratio of the travel time and travel costs marginal utility values. The Delta-method (Daly et al., 2012) is used to calculate the standard errors of the ratios. Table 0.57 shows the VOTTs of the three user groups of each final MNL model.

Table 0.57: The VOTTs estimated from the final MNL models.

Full sample MNL	*Value*	*Std. error*	*Value*
VOTT Car	0.147 [€/min]	0.0323	8.81 [€/hr]
VOTT CH with office interior	0.061 [€/min]	0.0129	3.66 [€/hr]
VOTT CH with leisure interior	0.098 [€/min]	0.0152	5.91 [€/hr]
Excl. non-traders MNL			
VOTT Car	0.139 [€/min]	0.0210	8.31 [€/hr]
VOTT CH with office interior	0.070 [€/min]	0.0117	4.22 [€/hr]
VOTT CH with leisure interior	0.104 [€/min]	0.0153	6.23 [€/hr]

All standard errors are acceptable low. The VOTT estimated for the chauffeur-driven office car users is lowest in both models: €3.66-4.22 per hour. Car users have the highest VOTT in both models as well. The full sample final MNL model estimates the VOTT on €8.81 per hour and the final MNL estimated from the data excluding non-traders provides a VOTT of €8.31 per hour. The ratio found for the chauffeur-driven leisure cars is approximately €6 per hour. The VOTT for car users approximates the VOTT found by Kouwenhoven et al. (2014) (€9 per hour) and Yap et al. (2016) (€9.30-9.90 per hour). A larger difference has been found with the VOTT found by Arentze & Molin (2013), which is €12.42-22.74 per hour.

First it is checked whether the VOTTs found per model differ significantly from each other. The results are shown in Table 0.58. Only the VOTT estimates of car users and chauffeur-driven office cars from the full-sample MNL model differ significantly from each other. However, in the second model the VOTT estimates of both chauffeur-driven car users differ significantly as well.

Table 0.58: Results Welch's t-test of the VOTTs within the final MNL models.

Full sample MNL	*t-value*	*df.*	
VOTT Car – VOTT CHO	2.46	316	Significant
VOTT Car – VOTT CHL	1.35	343	Not significant
VOTT CHO – VOTT CHL	1.87	469	Not significant
Excl. non-traders MNL			
VOTT Car – VOTT CHO	2.84	227	Significant
VOTT Car – VOTT CHL	0.68	265	Not significant
VOTT CHO – VOTT CHL	2.63	271	Significant

The largest discrepancy between two VOTTs of the same user group is 56 eurocents per hour (VOTT CH with office interior), while the smallest discrepancy is 32 eurocents per hour (VOTT

CH with leisure interior). Table 0.59 shows us the results of the Welch's t-test to determine whether the VOTTs between the final MNL model differ significantly from each other. All VOTTs of the same users groups estimated by the different models differ significantly. However, the VOTT of the car users is just significant.

Table 0.59: Results Welch's t-test of the VOTTs between the final MNL models..

	t-value	*df.*	
VOTT Car	3.03	384	Significant
VOTT CH with office interior	7.28	329	Significant
VOTT CH with leisure interior	14.05	305	Significant

CONCLUSIONS EXTENDED MNL MODELS

Now all the results are shown of the elaborated MNL models some conclusions can be drawn. Both models tell us that travelling alone is preferred over travelling with family/friends. First it is concluded that both comprehensive models have a better fitness than the base MNL models. Adding socio-economic variables and latent factors improve the explanation of the respondent's behaviour.

Thanks to the estimation results of both models is can be concluded that substituting travel time for working time is preferred over working extra time. Apparently, the respondents do not feel the necessity to work more than what they currently work. All the models (even the base MNL models) estimate that the VOTT for the users of the chauffeur-driven car with office interior is the lowest of the three modes that has been used in this experiment. Even users of the chauffeur-driven car with leisure interior are willing to pay less money to reduce their travel time in comparison to the car users. So from these outcomes it is concluded that the ability of performing an activity in a chauffeur-driven car reduces the VOTT of the users of the chauffeur-driven cars. Thereby, performing a working activity reduces the willingness to pay to reduce the travel time even more. This conclusion is enhanced by the significant latent factor *conveniences of automated driving*, which tells us that if one is able to profit from the conveniences of automated driven (e.g. work, have quality time, rest) he or she has a preference for the chauffeur-driven car. Furthermore it is observed that willingness to work in an AV has a relationship with preference for the chauffeur-driven car. From the full-sample final MNL model it is concluded that full-time workers have a preference for the chauffeur-driven cars, while the estimated models from the AV-case shows other behaviour, namely that full-time workers do not prefer AVs. Some other striking findings from the full-sample MNL model is that males prefer driving a car themselves. Furthermore, current car users have a preference for the chauffeur-driven cars, while current car users in the AV-case have a preference for the conventional car. However, the differences between the two cases is discussed later.

APPENDIX N: RESULTS CHAUFFEUR-CASE NESTED LOGIT MODELS

This appendix is dedicated to showing and discussing the results of the nested logit (NL) models. Two NL models are estimated with the chauffeur-case: one with the full sample and one with the sample excluding non-traders. Just as in the AV-case it is expected that the two chauffeur-driven cars belong to the same nest. Arguments are that both alternatives are not driven by the user, both alternatives provide the opportunity to be active, and last both alternatives have similarities in the name (chauffeur-driven car with red.). As explained in the theory about NL models a nest parameter will be estimated. If the nest parameter is one or does not significantly differ from one a normal MNL model is estimated. The final MNL models are used as base for the NL model estimation.

RESULTS NL MODELS

The statistics of both NL models are shown in Table 0.60. In both models one additional parameter is estimated, which is the nest parameter. The adjusted Rho-Square of an NL model estimated using the full sample has increased with 0.005, which means that the exploratory power has increased. The adjusted Rho-Square of the NL models (excl. non-traders) is almost similar to the value of the final MNL models (0.182).

Table 0.60: Statistics discrete choice NL model estimations.

	NL with full sample	*NL excl. non-traders*
Number of observations	2,904	1,752
Number of estimated parameters	22	16
Null log-likelihood	-3,190.370	-1,924.769
Final log-likelihood	-2,248.627	-1,559.707
Adjusted Rho-Square	0.292	0.181

The following table shows the results of the NL models where the two chauffeur-driven cars belong to the same nest. The alternatives chauffeur-driven car with office interior and chauffeur-driven car with leisure interior are nested in the parameter *chauffeur-driven*. The *normal car* parameter consists the conventional car alternative and is fixed on 1. In the full-sample NL model the nest parameter is 1.08. The NL model estimated from the data excluding non-traders estimated a nest parameter of one, meaning that the chauffeur-driven cars do not belong to the same nest. The t-test (0) tests the model in comparison to no model. The t-test(1) tests if the NL model differs from the MNL model. If the t-test (1) is significant, then there is a correlation between the unobserved utilities of the nested alternatives. In both models the t-test(1) is not significant, thus the NL models is in both cases not significantly different compared to the final MNL models.

Table 0.61: Nest parameters for CH-office & CH-leisure in the same nest.

Full sample NL	*Value*	*Std. error*	*t-test (0)*	*p-value*	*t-test (1)*	*p-value*
Normal car	1.00	-	-	-	-	-
Chauffeur-driven	1.08	0.222	4.87	0.00	0.38	0.70
Excl. non-traders NL						
Normal car	1.00	-	-	-	-	-
Chauffeur-driven	1.00	3.03e-08	3.3e+07	0.00	0.49	0.62

Because there is no correlation between the unobserved utilities of the chauffeur-driven alternatives the final MNL models are maintained. The estimated marginal utility coefficients are the same as in the final MNL models, so no tables of estimation results are provided.

Table 0.62 shows the results of the NL models in which the CH-office and the conventional car belong to the same nest. The results indicate that in the NL model estimating on the full data the CH-office alternative and the conventional car alternative belong to the same nest. This means that respondents experience commonalties between these two modes of transportation. A reason could be that in both alternatives one is able to work, although working in the conventional car is limited to making phone calls while driving.

Table 0.62: Nest parameters for CH-office & conventional car in the same nest.

Full sample NL	*Value*	*Std. error*	*t-test (0)*	*p-value*	*t-test (1)*	*p-value*
CH-leisure	1.00	-	-	-	-	-
CH-office & car	1.53	0.14	10.89	0.00	3.76	0.00
Excl. non-traders NL						
CH-leisure	1.00	-	-	-	-	-
CH-office & car	1.05	0.134	7.83	0.00	0.35	0.73

Table 0.63 presents the results of the NL models in which the CH-leisure and the conventional car belong to the same nest. None of the nest parameters is statistically significant. This means that a normal MNL model has been estimated. This outcome is according expectation.

Table 0.63: Nest parameters for CH-leisure & conventional car in the same nest.

Full sample NL	*Value*	*Std. error*	*t-test (0)*	*p-value*	*t-test (1)*	*p-value*
CH-office	1.00	-	-	-	-	-
CH-leisure & car	1.00	4.25e-08	2.35e+07	0.00	0.35	0.73
Excl. non-traders NL						
CH-office	1.00	-	-	-	-	-
CH-leisure & car	1.00	1.80e-308	0.00	1.00	0.00	1.00

Since one of the NL models estimated a significant nest parameter, the marginal valuations of the parameters have changed as well. Table 0.64 shows the estimation results of the other parameters of the significant NL model. All parameter values are in line with the outcomes of the MNL model. However, this model estimated the *Activity_CH_office* parameter insignificant, and therefore it equals 0.00. This means that no utility is experienced if one is working extra time or if one is substituting travel time for time at home. Another observation is that all parameter values are lower compared to the MNL model. This is due to the introduction of the nest parameter.

Table 0.64: Estimation results of the NL model with CH-office & conventional car in nest (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_CH*	0.446	0.416	1.07	0.28	0.554
Traveltime_CH_leisure	-0.0371	0.00495	-7.49	0.00	0.00505
Traveltime_CH_office	-0.0204	0.00482	-4.23	0.00	0.00477
Traveltime_car	-0.0212	0.00406	-5.23	0.00	0.0041
Travelcosts_CH_leisure	-0.406	0.0338	-12.01	0.00	0.0347
Travelcosts_CH_office	-0.387	0.0325	-11.92	0.00	0.0321
Travelcosts_car	-0.19	0.0429	-4.43	0.00	0.0423
Activity_CH_office*	-0.0531	0.0459	-1.16	0.25	0.0456
Travel_company_CH	-0.205	0.03	-6.83	0.00	0.0299
Travel_company_car	-0.146	0.0527	-2.78	0.01	0.0513
Walkingtime_car*	0.0294	0.0298	0.99	0.32	0.0298
AbleToWork_car	0.165	0.0409	4.04	0.00	0.041

WillingToWork_car	0.443	0.0477	9.29	0.00	0.0452
CarOwnership_car	-0.344	0.0976	-3.53	0.00	0.0894
Age2_car	-0.222	0.0749	-2.96	0.00	0.0764
Gender_car	0.141	0.0383	3.69	0.00	0.0393
Convenience_car	-0.554	0.0636	-8.71	0.00	0.0657
Safety_car	-0.254	0.0441	-5.75	0.00	0.0461
DO_other_car	0.205	0.0626	3.28	0.00	0.06
Mode_BMT_car	-0.579	0.151	-3.83	0.00	0.167
Mode_none_car	0.847	0.175	4.83	0.00	0.192

** = not significant in a 95% confidence interval*

The next step is calculating the mean VOTT estimates according the NL model results. The mean VOTT estimates are calculated by dividing the travel time parameter by the travel costs parameter. Table 0.65 shows the results of the mean VOTT estimates. All VOTT estimates are lower compared to the VOTT estimates of the MNL model. The biggest decease in VOTT estimate is VOTT of conventional car users: from 8.81 euro per hour according the MNL model to 6.69 euro per hour in the NL model.

Table 0.65: The VOTTs estimated from the NL model with CH-office & conventional car in a nest.

Full sample MNL	*Value*	*Std. error*	*Value*
VOTT Car	0.112 [€/min]	0.0228	6.69 [€/hr]
VOTT CH with office interior	0.053 [€/min]	0.0126	3.16 [€/hr]
VOTT CH with leisure interior	0.091 [€/min]	0.0152	5.48 [€/hr]

Table 0.66 shows the results of Welch's t-test. The t-test showed that the VOTT found for car travellers and for CH-leisure travellers do not differ significantly from each other in the 95% reliability interval.

Table 0.66: Results Welch's t-test of the VOTTs within the estimated NL model.

Full sample MNL	*t-value*	
VOTT Car – VOTT CHO	2.26	Significant
VOTT Car – VOTT CHL	0.74	Not significant
VOTT CHO – VOTT CHL	1.96	Significant

CONCLUSIONS NL MODELS

Given the datasets and the model outcomes the conclusion is drawn that the chauffeur-driven cars do not belong to the same nest. This result is not in line with the expectation. The same rhetoric could be applied to this results as for the NL result of the AV-case. The descriptions of the two chauffeur-driven alternatives is written down in such a way that respondents experience these alternatives as different modes of transportation. The descriptions of the chauffeur-driven cars was exactly the same as the AVs, with the exception that the automated driving part was substituted with a costless chauffeur.

However, we can conclude that the chauffeur-driven office car and the conventional car do belong to the same nest. Though, the nest parameter is only significant when the NL model is estimated using the full sample. The commonalities of both modes is that in both modes of transport one is able to work. Despite the CH-office offers an environment in which one is able to do more working activities than making phone calls, the conventional car and CH-office are partly experienced the same.

APPENDIX O: RESULTS AV-CASE ERROR-COMPONENT MIXED LOGIT WITH PANEL EFFECT MODELS

Just as in the AV-case two error-component ML with panel effect models are estimated on the chauffeur-case data. The error-component ML model assumes that the alternative-specific constants (α) are randomly distributed instead of being fixed. The final MNL models are used as base for the error-component models. The alternative-specific constant of the chauffeur-driven cars in the utility functions Equation 54 and Equation 55 is altered as follows:

Equation 57

$$\alpha_{CH} \sim N(\alpha_{CH}, \sigma_{\alpha_{CH}})$$

Where α_{CH} represents the alternative-specific constant, and σ_{α_CH} the degree of variation. Again, first the results of regarding the full sample is shown followed up by the results estimated on the data excluding non-traders.

RESULTS ERROR-COMPONENT ML MODELS

1000 Draws are used to estimate the models, where the full sample model requires 988 iterations to reach convergence and the other model 400. Table 0.67 shows the statistics of the estimated error-component ML models. The adjusted Rho-Square has been improved regarding both models. With respect to the full sample it improves from 0.289 in the final MNL model to 0.411 in the error-component ML with panel effect model. When excluding the non-traders the adjusted Rho-square is improved from 0.182 to 0.196.

Table 0.67: Statistics discrete choice error-component ML model estimations.

	Error-comp. full sample	*Error-comp. excl. non-traders*
Number of observations	2,904	1,752
Number of estimated parameters	22	16
Number of individuals	242	146
Null log-likelihood	-3,189.370	-1,924.769
Final log-likelihood	-1,857.658	-1,532.086
Adjusted Rho-Square	0.411	0.196

Table 0.68 shows the results of the estimated error-component model on the full sample. Eight estimated parameters are not significant. No significant preference for the chauffeur-driven car has been observed. On the other hand, the degree of variation in unobserved preference for chauffeur-driven cars (sigma) is significant. This means that there is significant and substantial heterogeneity. So, if one of the chauffeur-driven alternatives improves it has more effect on the other chauffeur-driven alternative rather than the car alternative.

The marginal value for travel time for a trip in the chauffeur-driven leisure car is higher (-0.0718) than for a trip made in a normal car (-0.0602) or the chauffeur-driven office car (-0.0401). This indicates that people travelling with the office-car are less time sensitive. Regarding the marginal utility value of travel costs travellers of the chauffeur-driven office car are more sensitive (-0.601) compared to car travellers (-0.448) or leisure-car travellers (-0.494). Thus regarding costs, chauffeur-driven office users are 34% more sensitive than car users and 22% more sensitive than chauffeur-driven leisure car users. Again, working additional time in a chauffeur-driven car is not add marginal utility (-0.211). Travelling with travel companions is valued negatively as well in all modes (car: -0.301, CH: -0.132). Seemingly, travelling with known companions in a car is valued more than twice as negatively than in a chauffeur-driven car. An increase in walking time is adds utility (0.108) to the car alternative rather than disutility. This outcome is not consistent with reality and is considered as an error. Further it is indicated that if one is not willing to work in an AV, he or she has a preference for the car alternative (1.10) over the chauffeur-driven alternatives. The importance of the attitudinal latent factors are shown in the results as well. In the case a respondents has a positive attitude towards the conveniences of automated driving and the safety of automated driving one does not prefer the conventional car (-1.60 and -0.649 respectively).

The coefficient of the age indicator regards the age category 26-60 years is insignificant, thus its marginal utility value equals 0.00. The same holds for gender. The marginal utility coefficients regarding daily occupation and most commonly used mode are not significant as well, and therefore equals 0.00.

Table 0.68: Estimation results the error-component ML with panel effect model (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_CH*	-0.952	0.981	-0.97	0.33	0.839
Sigma_constant_CH	-2.74	0.219	-12.51	0.00	0.234
Traveltime_CH_leisure	-0.0718	0.00688	-10.43	0.00	0.00824
Traveltime_CH_office	-0.0401	0.00646	-6.21	0.00	0.00582
Traveltime_car	-0.0602	0.00681	-8.84	0.00	0.00774
Travelcosts_CH_leisure	-0.494	0.0394	-12.53	0.00	0.0472
Travelcosts_CH_office	-0.601	0.0382	-15.73	0.00	0.0489
Travelcosts_car	-0.448	0.0731	-6.13	0.00	0.0735
Activity_CH_office	-0.211	0.0639	-3.3	0.00	0.0488
Travel_company_CH	-0.132	0.0381	-3.46	0.00	0.0357
Travel_company_car	-0.301	0.0841	-3.58	0.00	0.0728
Walkingtime_car	0.108	0.0463	2.34	0.02	0.0451
AbleToWork_car*	0.471	0.241	1.96	0.05	0.231
WillingToWork_car	1.1	0.247	4.44	0.00	0.239
CarOwnership_car*	-0.759	0.587	-1.29	0.20	0.439
Age2_car*	-0.438	0.458	-0.96	0.34	0.484
Gender_car*	0.354	0.222	1.59	0.11	0.223
Convenience_car	-1.60	0.273	-5.85	0.00	0.262
Safety_car	-0.649	0.242	-2.68	0.01	0.262
DO_other_car*	0.528	0.382	1.38	0.17	0.413
Mode_BMT_car*	-1.13	0.867	-1.3	0.19	1.12
Mode_none_car*	1.46	0.93	1.57	0.12	1.21

** = not significant in a 95% confidence interval*

Next, the estimation results of the error-component model estimated on data excluding non-traders are shown and discussed. Table 0.69 indicates that an increase in travel time add least disutility when travelling in the chauffeur-driven office car (-0.071) compared to travelling in the normal car (-0.591) and the chauffeur-driven leisure car (-0.0722). The marginal value for travel costs when driving in a car is lower (-0.432) than when one is driving in a chauffeur-driven leisure car (-0.554) or an office car (-0.661). This indicates that car users are less cost-sensitive. Just as indicated in the previous model, working additional time is valued negatively over saving time at the office in the chauffeur-driven car (-0.209). Travelling with others is also experienced negatively compared to travelling alone (car: -0.285, CH: -0.178). The non-logical positive walking time coefficient is not significant, and therefore equals 0.00. The car alternative is preferred by people who are not willing to work in a vehicle (0.307). Owning a car add no significant utility to either car or chauffeur-driven alternative, and thus equals 0.00. The importance of attitudinal factors is shown in this model as well. Respondents with a positive attitude regarding conveniences of automated driving and the safety aspects of automated driving have a preference for the chauffeur-driven car.

Table 0.69: Estimation results of the error-component ML with panel effect model (excl. non-traders).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_CH*	1.39	0.761	1.83	0.07	0.696
Sigma_constant_CH	-0.803	0.0955	-8.41	0.00	0.0961
Traveltime_CH_leisure	-0.0722	0.00701	-10.29	0.00	0.00846
Traveltime_CH_office	-0.0471	0.00715	-6.59	0.00	0.00692
Traveltime_car	-0.0591	0.00691	-8.55	0.00	0.00776
Travelcosts_CH_leisure	-0.554	0.043	-12.87	0.00	0.0522
Travelcosts_CH_office	-0.661	0.0403	-16.41	0.00	0.0524
Travelcosts_car	-0.432	0.0773	-5.59	0.00	0.0794
Activity_CH_office	-0.209	0.0689	-3.04	0.00	0.0552
Travel_company_CH	-0.178	0.0419	-4.26	0.00	0.0408
Travel_company_car	-0.285	0.0854	-3.34	0.00	0.0739
Walkingtime_car*	0.0614	0.0469	1.31	0.19	0.0455
WillingToWork_car	0.307	0.0983	3.12	0.00	0.0925
CarOwnership_car*	-0.335	0.235	-1.43	0.15	0.194
Convenience_car	-0.335	0.134	-2.5	0.01	0.13
Safety_car	-0.208	0.105	-1.97	0.05	0.101

** = not significant in a 95% confidence interval*

Next step is computing the VOTT parameters for the three user groups per model estimation. It is assumed that the travel time and travel costs parameters are linear-additive, such that the VOTT is determined by the ratio of these two components. Table 0.70 indicates that the VOTT of the chauffeur-driven office car users is lower than the users of the comparison modes. Furthermore, all the ratios are significant given the low standard errors. However the error-component model estimated on the full sample indicates that the VOTT of car users is lower than the leisure-car users, while the model estimated on data excluding non-traders indicates the opposite.

The VOTT estimates are slightly under the estimates of Kouwenhoven et al. (2014) and Yap et al. (2016). The car users VOTTs are about 33% lower than the values determined by Arentze & Molin (2013).

Table 0.70: The VOTTs estimated from the error-component ML with panel effect models.

Full sample error-comp. ML	*Value*	*Std. error*	*Value*
VOTT Car	0.134 [€/min]	0.0174	8.06 [€/hr]
VOTT CH with office interior	0.067 [€/min]	0.0112	4.00 [€/hr]
VOTT CH with leisure interior	0.145 [€/min]	0.0176	8.72 [€/hr]
Excl. non-traders error-comp. ML			
VOTT Car	0.137 [€/min]	0.0188	8.21 [€/hr]
VOTT CH with office interior	0.071 [€/min]	0.0113	4.28 [€/hr]
VOTT CH with leisure interior	0.130 [€/min]	0.0157	7.82 [€/hr]

Next step is to determine whether the estimated VOTTs differ significantly from each other within each error-component ML model. Table 0.71 indicates that the VOTT found for car users and for the chauffeur-driven leisure car do not differ significantly from each other in both models. In both models the VOTT of people travelling with the chauffeur-driven office car differs significantly from the VOTTs of the car travellers and the leisure-car travellers.

Table 0.71: Results Welch's t-test of the VOTTs within the error-component ML with panel effect models.

Full sample error-comp. ML	*t-value*	*df.*	
VOTT Car – VOTT CHO	2.99	238	Significant
VOTT Car – VOTT CHL	0.26	281	Not significant
VOTT CHO – VOTT CHL	3.05	264	Significant
Excl. non-traders error-comp. ML			
VOTT Car – VOTT CHO	3.26	412	Significant
VOTT Car – VOTT CHL	0.44	482	Not significant
VOTT CHO – VOTT CHL	3.77	409	Significant

The determined values of travel time estimates in the model estimated on the full sample and the model estimated on data excluding non-traders per users group are almost similar or at least close to each other. Table 0.72 shows that the VOTT estimates of car users do not differ significantly from each other in a 95% reliability interval, thus the found values can be considered the same. The VOTT estimates of the chauffeur-driven office car and the chauffeur-driven leisure car users do differ significantly.

Table 0.72: Results Welch's t-test of the VOTTs between the error-component ML with panel effect models..

	t-value	*df.*	
VOTT Car	1.27	288	Not significant
VOTT CH with office interior	3.83	303	Significant
VOTT CH with leisure interior	8.72	333	Significant

CONCLUSIONS ERROR-COMPONENT ML MODELS

Based on these results some conclusion can be drawn. It can be concluded that despite no mean preference for the chauffeur-driven car has been observed significant and substantial heterogeneity exists within the chauffeur-driven car alternatives. Furthermore, since one of the objectives of this study is to explore whether the trip appreciation in a AV is different than in a human-driven car the VOTT estimates are evaluated. In both models (full sample and excl. non-traders) it is indicated that travellers with the chauffeur-driven office car are willing to pay less money compared to people who travel with a normal car or a chauffeur-driven leisure car. Unfortunately, no statement can be given if car users are willing to pay more money to reduce travel time in comparison to chauffeur-driven leisure users. The lower VOTT for the chauffeur-driven office car is according expectation, since people could work in the redesigned interior. In the case people tend to choose the office-car it is concluded that he or she prefers saving time at the office instead of working extra time. Apparently the benefits of earning extra money or spare days does not weight to substituting travel time for time at home. Next, it is concluded that travellers prefer to travel alone during the morning peak regardless of the used mode. At last it is based on these results that attitudinal factors matter in travel behaviour. Having a positive attitude regarding the conveniences of automated driving and the safety of automated driving increases the utility of chauffeur-driven modes, and therefore the probability of choosing this mode of transportation.

APPENDIX P: RESULTS CHAUFFEUR-CASE MIXED LOGIT WITH PANEL EFFECT MODELS

In this appendix the results of the estimated taste mixed logit with panel effect models with panel effect are discussed. As already discussed the sensitivity for certain taste parameters differ across people. For example, one person is more time- or cost sensitive than another. As already argued these taste ML models assume a normal distribution in the mode-specific time coefficients. Only ML models with a normal distribution are estimated, since one model estimated took around 10 hours. So, to estimate this type of ML model the utility functions are modified such that:

Equation 58

$$\beta_{TT\_CAR} \sim N(\beta_{TT\_CAR}, \sigma_{\beta_{TT\_CAR}})$$

Equation 59

$$\beta_{TT\_CHO} \sim N(\beta_{TT\_CHO}, \sigma_{\beta_{TT\_CHO}})$$

Equation 60

$$\beta_{TT\_CHL} \sim N(\beta_{TT\_CHL}, \sigma_{\beta_{TT\_CHL}})$$

Where the β_{TT} is the mode-specific parameter for travel time (mean taste), and the σ_{β} us the degree of unobserved taste variation for travel time. If all the estimated sigmas are insignificant, then the ML model becomes a MNL model. Then, no individual-specific variation in unobserved taste is measured. Two models are estimated: one on the full sample and one on the sample excluding non-traders. First the panel-ML model estimated with all data is discussed. Subsequently the estimated model from data excluding non-traders is estimated.

RESULTS ML WITH PANEL EFFECT MODELS

Table 0.73 shows that the number of estimated parameters is 24 for the full-sample model and 18 for the other model. The final log-likelihoods are improved compared to the MNL models and the error-component models. It results in a very high adjusted rho-square of 0.455 for the ML model estimated on the full sample, and in a reasonably well adjusted Rho-square of 0.219 for the ML model estimated on the sample excluding non-traders.

Table 0.73: Statistics discrete choice ML with panel effect model estimations.

	ML with full sample	*ML excl. non-traders*
Number of observations	2,904	1,752
Number of estimated parameters	24	18
Number of individuals	242	146
Null log-likelihood	-3,190.370	-1,924.769
Final log-likelihood	-1,712.869	-1,486.101
Adjusted Rho-Square	0.455	0.219

The ASC for the chauffeur-driven car alternatives is insignificant, and therefore equals 0.00. This means that no unobserved preference is observed for the chauffeur-driven car. Travellers by car have a lower marginal utility value for travel time (-0.0402) compared to the office car users (-0.0765) and the leisure car users (-0.109). All estimated sigmas are significant, thus there exists heterogeneity in the mode-specific travel time parameters. However, the sigmas itself are relatively low. People travelling with the chauffeur-driven office car are most costs sensitive (-0.809) compared to car travellers (-0.487) and leisure car travellers (-0.722). A preference is measured for travelling alone in all modes (car: -0.221, CH: -0.278 for travelling with friends/family). As working activity in the chauffeur-driven office car is it preferred to save time at the office over working additional time. Walking time has not been valued significantly, and equals 0.00. Being able to work in an comfortable car without trepidation is valued negatively when travelling with a normal car (0.421 * -1 = -0.421). The same valuation has been observed regarding willing to work in an AV (0.801 * -1 = -0.801). The parameter that provides a marginal utility value to car ownership is not significant anymore, and therefore equals 0.00. The indicators of the age category 26-60, the commonly used modes, and the daily occupation 'other' are insignificant as well and also equal a marginal utility of zero. Being a male, on the other hand, reflects a preference for the normal car (0.338), however females have a negative attitude towards car (-0.338) compared to the chauffeur-driven cars. The attitudinal factors conveniences of automated driving and safety in an AV are important in the behaviour of the respondents. A positive attitude towards these two latent factors results in a negative valuation of the car alternative with respect to the chauffeur-driven alternatives.

Table 0.74: Estimation results the ML with panel effect model (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_CH*	1.38	0.93	1.49	0.14	0.878
Traveltime_CH_leisure	-0.109	0.00993	-10.96	0.00	0.0113
Traveltime_CH_office	-0.0765	0.00989	-7.73	0.00	0.00956
Traveltime_car	-0.0402	0.0106	-3.81	0.00	0.011
Sigma_traveltime_CHL	-0.0566	0.00645	-8.77	0.00	0.00686
Sigma_traveltime_CHO	-0.0575	0.00675	-8.51	0.00	0.00888
Sigma_traveltime_car	0.106	0.00997	10.62	0.00	0.0117
Travelcosts_CH_leisure	-0.722	0.0516	-14	0	0.0664
Travelcosts_CH_office	-0.809	0.0484	-16.72	0	0.0677
Travelcosts_car	-0.487	0.0828	-5.88	0.00	0.0888
Activity_CH_office	-0.258	0.0766	-3.37	0	0.0678
Travel_company_CH	-0.221	0.047	-4.7	0	0.0485
Travel_company_car	-0.278	0.0923	-3.01	0	0.0843
Walkingtime_car*	0.0829	0.051	1.63	0.10	0.0534
AbleToWork_car	0.421	0.187	2.25	0.02	0.21
WillingToWork_car	0.801	0.185	4.33	0.00	0.202
CarOwnership_car*	-0.747	0.389	-1.92	0.05	0.291
Age2_car*	-0.342	0.368	-0.93	0.35	0.443
Gender_car	0.338	0.171	1.97	0.05	0.187
Convenience_car	-1.27	0.23	-5.53	0.00	0.284
Safety_car	-0.587	0.188	-3.12	0.00	0.239
DO_other_car*	0.174	0.3	0.58	0.56	0.308
Mode_BMT_car*	-0.607	0.643	-0.94	0.34	0.659
Mode_none_car*	1.16	0.686	1.69	0.09	0.642

** = not significant in a 95% confidence interval*

The model results indicate that there is an unobserved preference for the chauffeur-driven car (2.64). Table 0.75 shows significant values for the mean time parameters as well as for the corresponding standard deviations. This means that there is heterogeneity in the mode-specific time parameters. The marginal utility decrease due to an increase in travel time is highest when travelling with a chauffeur-driven leisure car (-0.0887) compared to the chauffeur-driven office car

(-0.0662) and the conventional car (-0.0611). The marginal utility coefficient regarding travel costs is lowest for the normal car (-0.403) with respect to the chauffeur-driven office car (-0.761) and the leisure car (-0.669). Travelling with family/friends is valued negatively in all modes compared to travelling alone (car: -0.25, CH: -0.216). As working activity a preference is observed for saving time at the office rather than working additional time (-0.246). No significant parameter for walking time is estimated, thus it equals 0.00. In the case one is willing to work in an AV a negative valuation is given regarding the car alternative (-1 * 0.323 = -0.323) compared to the other alternatives. Owning a car does not make a significant difference in utility valuation of the alternatives. Only a positive attitude regarding the conveniences of automated driving influences the choice behaviour. Persons having a positive attitude towards the conveniences of automated driving prefer a chauffeur-driven car over the normal car.

Table 0.75: Estimation results of the error-component ML with panel effect model (excl. non-traders).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_CH	2.64	0.827	3.19	0.00	0.789
Traveltime_CH_leisure	-0.0887	0.00849	-10.45	0.00	0.00989
Traveltime_CH_office	-0.0662	0.00866	-7.64	0.00	0.00853
Traveltime_car	-0.0611	0.00779	-7.84	0.00	0.00852
Sigma_traveltime_CHL	0.0304	0.00433	7.02	0.00	0.0044
Sigma_traveltime_CHO	-0.0315	0.00444	-7.11	0.00	0.00494
Sigma_traveltime_car	0.0301	0.0044	6.85	0.00	0.045
Travelcosts_CH_leisure	-0.669	0.0492	-13.58	0.00	0.0605
Travelcosts_CH_office	-0.761	0.0458	-16.62	0.00	0.0611
Travelcosts_car	-0.403	0.0808	-5.00	0.00	0.0842
Activity_CH_office	-0.246	0.0752	-3.27	0.00	0.0651
Travel_company_CH	-0.216	0.0457	-4.71	0.00	0.0466
Travel_company_car	-0.25	0.0893	-2.8	0.01	0.08
Walkingtime_car*	0.056	0.0493	1.14	0.26	0.0499
WillingToWork_car	0.323	0.114	2.83	0.00	0.104
CarOwnership_car*	-0.492	0.279	-1.76	0.08	0.221
Convenience_car	-0.402	0.153	-2.63	0.01	0.146
Safety_car*	-0.227	0.121	-1.88	0.06	0.119

** = not significant in a 95% confidence interval*

Now the mean travel time parameters with their corresponding standard deviations are known the VOTT distribution per users group per model can be computed. The explanation of how to compute the mean-VOTT and the standard deviation has been given before. Table 0.76 shows the mean VOTTs with corresponding standard deviations. A large discrepancy is observed in the mean VOTT and the standard deviation for car users in the full-sample ML model and the excluding non-traders model. The mean VOTT estimate for car travellers is almost doubled in the case it is determined with the ML estimated on data excluding non-traders. In both models the mean VOTT estimate of the office car users is around €5.50 per hour. The mean VOTT estimate of the chauffeur-driven leisure car users is €9.06 per hour according the full-sample model and €7.96 per hour according the model estimated on the sample excluding non-traders.

The mean VOTT found for car drivers in the model estimated on data excluding non-traders approach the values of Kouwenhoven et al. (2014) and Yap et al. (2016), which are €9.00 per hour and €9.30-9.90 per hour respectively. The car user VOTT found in Arentze & Molin (2013) is much higher (€12.42 - €22.74) than these values. The estimate mean VOTT for car users in the first ML model is unlikely low.

Table 0.76: VOTT estimates with standard deviation from the ML with panel effect models.

Full sample panel ML	*Value*	*Std. dev*	*Value*	*Std. dev*
VOTT Car	0.083 [€/min]	0.218	4.95 [€/hr]	13.06
VOTT CH-office	0.095 [€/min]	0.071	5.67 [€/hr]	4.26
VOTT CH-leisure	0.151 [€/min]	0.078	9.06 [€/hr]	4.70
Excl. non-traders ML				
VOTT Car	0.152 [€/min]	0.0747	9.10 [€/hr]	4.48
VOTT CH-office	0.087 [€/min]	0.0414	5.22 [€/hr]	2.48
VOTT CH-leisure	0.133 [€/min]	0.0454	7.96 [€/hr]	2.73

Again a probability occurs that a positive travel time parameters is observed, since the travel time parameter follows a normal distribution. Figure 0.6 shows the probability density functions of the mode-specific time parameters estimated on the full sample. The probability that the car-specific time parameter becomes positive is not acceptable large: 35.2%. The occurrence of a positive travel time parameter for the chauffeur-driven office car is 9.2% and for the chauffeur-driven leisure car is 2.7%. This high probability of a positive travel time parameter estimation is not surprising given the relatively large standard deviation. The normal distributions of the chauffeur-driven travel time parameters are more narrow due to lower standard deviations.

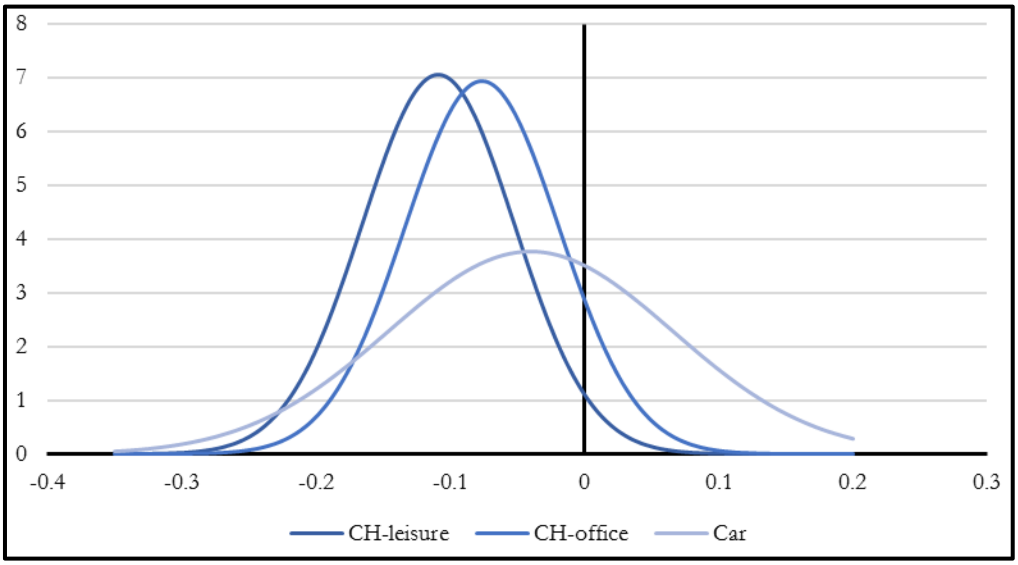

Figure 0.6: Probability density function β_{TT} ML with panel effect model (full sample).

To illustrate the bound of the different distributions, 95% quantile bounds for the VOTTs were calculated. Table 0.77 indicates that in the lower 95% quantile limit a VOTT estimation of €-20.64 per hour could occur for car travellers. This is contrary to all theory. The lower bound of the chauffeur-driven cars contains a negative VOTT value as well. Despite it is much closer to zero it is not realistic. Again a higher obtained adjusted Rho-Square does not mean better estimated VOTT estimates.

Table 0.77: 95% quantile intervals for the distribution of the VOTTs (full sample).

	Lower 95% quantile limit	*Upper 95% quantile limit*
β_{TT_CAR}	-20.64 [€/hr]	30.55 [€/hr]
$\beta_{TT\_CH\text{-}OFFICE}$	-2.68 [€/hr]	14.03 [€/hr]
$\beta_{TT\_CH\text{-}LEISURE}$	-0.16 [€/hr]	18.28 [€/hr]

At last a graph with the probability density functions of the mode-specific travel time parameters estimated on the data excluding non-traders is provided. Figure 0.7 shows us that the probability of positive parameters given the normal distributions is much lower than in the previous case. A probability of 2.1% is observed for a positive car-parameter. The probability of a positive chauffeur-driven office car or leisure car time parameter is 1.8% and 0.2% respectively. Despite the fact that a probability occurs of measuring a positive travel time parameter, and thus a negative VOTT estimate, the reliability is high.

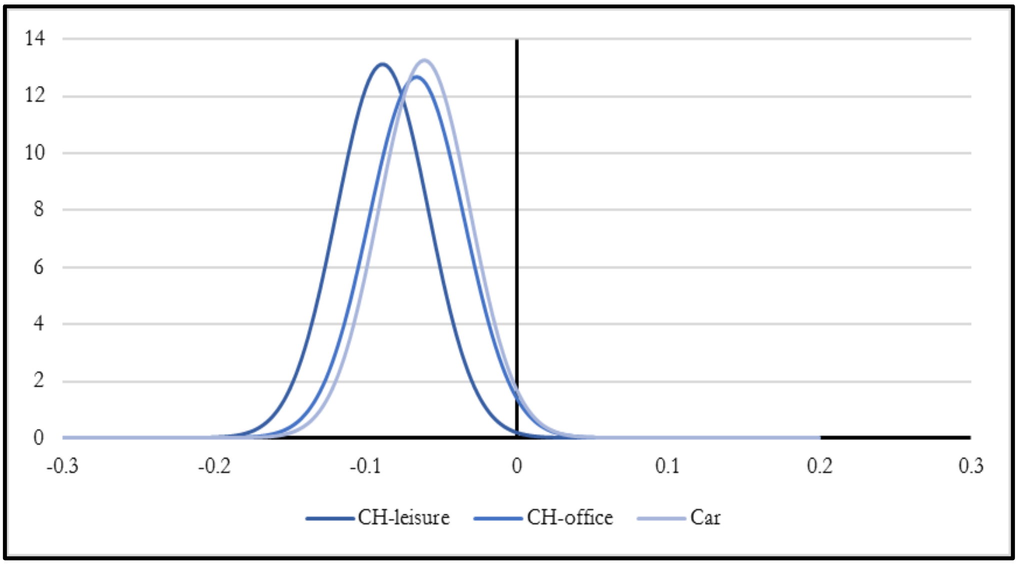

Figure 0.7: Probability density function β_{TT} ML with panel effect model (excl. non-traders).

The higher reliability of these outcomes is supported by the 95% quantile bounds for the VOTT distributions. All VOTT values of all the user groups within the 95% reliability interval are positive. This could mean that the improvement in adjusted Rho-Square contributes to better VOTT estimates, despite using a normal distribution for the travel time parameters.

Table 0.78: 95% quantile intervals for the distribution of the VOTTs (excl. non-traders).

	Lower 95% quantile limit	*Upper 95% quantile limit*
β_{TT_CAR}	0.31 [€/hr]	17.88 [€/hr]
$\beta_{TT\_CH\text{-}OFFICE}$	0.35 [€/hr]	10.09 [€/hr]
$\beta_{TT\_CH\text{-}LEISURE}$	2.61 [€/hr]	13.30 [€/hr]

CONCLUSIONS ML WITH PANEL EFFECT MODELS

The last paragraph of this appendix draws conclusions of the ML with panel effect model. The first conclusion is that the performance of the ML with panel effect models has been improved compared to their MNL equivalents. However, it goes with the detriment of the reliability of the VOTT parameters.

First, the model results tell us that heterogeneity exists within the travel time, although in the model estimated on the full data more heterogeneity is observed than in the model that excludes non-traders. In fact, the found standard deviations of the model that excludes non-traders are almost half the values found in the full-sample model. The mean VOTT estimate for chauffeur-driven office car users is lower than the mean VOTT estimate of car users and of AV-leisure users according both model results. However, taking the normal distribution of the VOTTs into account it must be said that the reliability of the outcomes produced by the model estimated on data excluding non-traders is much more reliable. High probabilities (2.7% - 35.2%) occur of estimating a negative VOTT estimate for all user groups in the full-sample model, whereas the highest probability of estimating a negative VOTT in the latter model is 2.1%. According the results provided by the full-sample model the leisure-car users have a substantial higher mean VOTT, while the model that excludes non-traders indicate otherwise. However, the model estimated on the sample excluding non-traders shows much more reliable results given all positive VOTT estimates in the 95% reliability interval, so it is concluded that this model produces better VOTT estimates. Thus we can conclude that excluding non-traders improves the VOTT estimates and that despite a big improvement in the adjusted Rho-Square, drawing conclusions on normal distributed VOTT estimates is still risky.

APPENDIX Q: RESULTS CHAUFFEUR-CASE COMBINED MIXED LOGIT WITH PANEL EFFECT MODELS

The error-component model and the taste ML model are combined and discussed in this appendix. All the travel time parameters follow a normal distribution where the model estimates the mean travel time parameters and the standard deviations. Also the alternative-specific constant for the chauffeur-driven cars is normally distributed.

RESULTS COMBINED ML WITH PANEL EFFECT MODELS

Table 0.79 provides us the results of the combined ML models. Testing heterogeneity in the alternative specific constant and the travel time parameters leads to a lower adjusted Rho-Square in the model that is estimated on the sample excluding non-traders. The standard deviation of the ASC is not significant, thus the ML model with only normal distributed travel time parameters was estimated. So, this model (excl. non-traders) is not further discussed in this appendix. The model estimated on the full sample improved in both log-likelihood and in the adjusted Rho-Square. The model estimates are discussed below.

Table 0.79: Statistics discrete choice combined ML with panel effect model estimations.

	ML with full sample	*ML excl. non-traders*
Number of observations	2,904	1,752
Number of estimated parameters	25	19
Number of individuals	242	146
Null log-likelihood	-3,190.370	-1,924.769
Final log-likelihood	-1,704.906	-1,486.804
Adjusted Rho-Square	0.458	0.218

The estimation results of the ML model estimated on the full sample are shown in Table 0.80. It indicates that all standard deviations are significant, meaning that in all normal distributed parameters is heterogeneity observed. However, the mean parameter regarding the preference for a chauffeur-driven car is not significant, and therefore equals 0.00. An increase in travel time is on average valued lower in a normal car (-0.0539) in comparison to the office car (-0.767) and the leisure car (-0.108). The largest heterogeneity in a time parameter has been observed in car's travel time parameter. An increase in travel costs is experienced worse when travelling with the chauffeur-driven office car (-0.82) compared to the car (-0.488) and the leisure car (-0.731). Again, saving time at the office is preferred over working extra time (-0.284). Also travelling alone has a preference over travelling with family/friends in all modes. The walking time, which is surprisingly positive valued, is not significant and equals zero. Car ownership and being able to work in a car with high comfort and internet, and without vibrations are not significantly valued. In the case one is willing to work in an AV, disutility regarding the car alternative is indicated (1.01 * -1 = -1.01). The influence of age and gender are not found significant, and equals 0.00. Two attitudinal factors are found significant, and thus provides insight in the choice behaviour. If a respondent has a positive attitude towards the conveniences of automated driving and the safety of automated driving a preference for the chauffeur driven car has been observed. Socio-economic variables like *daily occupation* and *commonly used mode* are not significant.

Table 0.80: Estimation results the combined ML with panel effect model (full sample).

Parameter	*Value*	*Std. error*	*T-value*	*P-value*	*Robust std. error*
Constant_car	0.00	-	-	-	-
Constant_CH*	0.883	1.1	0.8	0.42	1.2
Sigma_constant_CH	-2.01	0.428	-4.68	0.00	0.69
Traveltime_CH_leisure	-0.108	0.0102	-10.56	0.00	0.0131
Traveltime_CH_office	-0.0767	0.0098	-7.83	0.00	0.0103
Traveltime_car	-0.0539	0.0107	-5.04	0.00	0.0121
Sigma_traveltime_CHL	0.0554	0.00652	8.5	0.00	0.00816
Sigma_traveltime_CHO	0.0575	0.00632	9.1	0.00	0.00809
Sigma_traveltime_car	0.083	0.0125	6.63	0.00	0.0214
Travelcosts_CH_leisure	-0.731	0.0531	-13.77	0.00	0.0713
Travelcosts_CH_office	-0.82	0.0495	-16.57	0.00	0.0707
Travelcosts_car	-0.488	0.0846	-5.76	0.00	0.0912
Activity_CH_office	-0.284	0.0773	-3.68	0.00	0.0687
Travel_company_CH	-0.213	0.047	-4.53	0.00	0.0482
Travel_company_car	-0.3	0.0941	-3.19	0.00	0.0885
Walkingtime_car*	0.0886	0.0516	1.72	0.09	0.0546
AbleToWork_car*	0.411	0.218	1.89	0.06	0.205
WillingToWork_car	1.01	0.227	4.44	0.00	0.226
CarOwnership_car*	-0.809	0.556	-1.46	0.15	0.449
Age2_car*	-0.395	0.529	-0.75	0.46	0.759
Gender_car*	0.35	0.209	1.68	0.09	0.224
Convenience_car	-1.81	0.363	-5.0	0.00	0.508
Safety_car	-0.713	0.3	-2.38	0.02	0.433
DO_other_car*	0.214	0.421	0.51	0.61	0.522
Mode_BMT_car*	-0.349	1.14	-0.31	0.76	1.6
Mode_none_car*	0.919	1.26	0.73	0.46	1.68

** = not significant in a 95% confidence+ interval*

Table 0.81 provides us the mean VOTT estimates and its standard deviations. The mean VOTT of the chauffeur-driven office car users is the lowest compared to the other two traveller types. The VOTT of the car users is more widespread distributed seen the larger standard deviation. This means that this estimate could provide false information. Having a large standard deviation is not per definition wrong, however there occurs a probability of having a positive travel time parameter, which is absolutely not desirable.

Table 0.81: VOTT estimates with standard deviation from the combined ML with panel effect model.

Full sample panel ML	*Value*	*Std. dev*	*Value*	*Std. dev*
VOTT Car	0.110 [€/min]	0.170	6.63 [€/hr]	10.20
VOTT CH-office	0.094 [€/min]	0.070	5.61 [€/hr]	4.21
VOTT CH-leisure	0.148 [€/min]	0.076	8.86 [€/hr]	4.55

Figure 0.8 shows us the probability density function of the mode-specific travel time parameters. This graph support the statement that a higher standard deviation could lead to false conclusions. This figure indicates that a large probability occurs that the travel time parameter of car travellers is positive (25.8%), which is not logical and correct. The probability of a non-negative travel time parameters for chauffeur-driven office car travellers is 9.1% and of the leisure car users 2.6%.

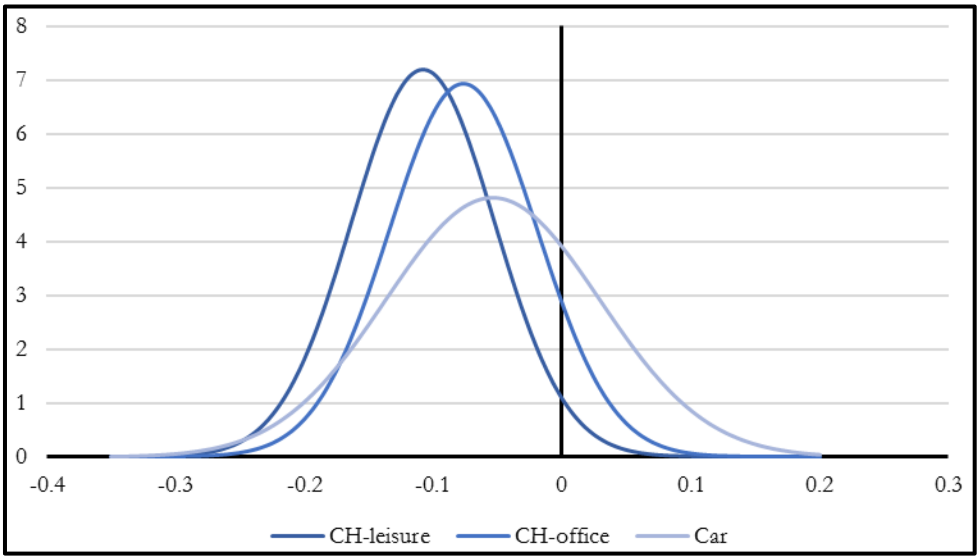

Figure 0.8: Probability density function β_{TT} combined ML with panel effect model (full sample).

As last example, the 95% quantile intervals of the three VOTT ratios are calculated and shown in Table 0.82. This table indicates that all three the VOTT distribution have a probability of having a negative VOTT parameter within the 95% reliability interval. It indicates that the probability of estimating a negative VOTT is notably smaller for the two chauffeur-driven cars compared to the conventional car.

Table 0.82: 95% quantile intervals for the distribution of the VOTTs (full sample).

	Lower 95% quantile limit	*Upper 95% quantile limit*
β_{TT_CAR}	-13.37 [€/hr]	26.63 [€/hr]
$\beta_{TT\_CH\text{-}OFFICE}$	-2.63 [€/hr]	13.86 [€/hr]
$\beta_{TT\_CH\text{-}LEISURE}$	-0.05 [€/hr]	17.78 [€/hr]

CONCLUSIONS ML WITH PANEL EFFECT MODELS

We can conclude that combining the error-component ML and the taste ML model does not improve in model fit for both datasets. Only an improvement in adjusted Rho-Square has been made with the model estimated on the full sample. The model results indicate that heterogeneity exists in the alternative specific constant as well as in all the travel time parameters. So, it is concluded that variety exists in time valuation (and thus in the VOTT) and regarding the mode-specific parameter.

Given the model output it can be said that travellers with the chauffeur-driven office can have the lowest mean VOTT in comparison to the car travellers and the leisure car travellers. The improvement in adjusted Rho-Square comes with an improvement in the probability of having positive travel time parameters. However, given the nature of the normal distribution a probability exists that one of the travel time parameters is estimated positively, which results in a negative VOTT. This probability is the highest for the VOTT of car travellers and therefore conclusions based on this distribution is most risky. So, drawing hard conclusion from normally distributed VOTT estimates is hard. However, it indicates that office car users have the lowest mean VOTT, then the car users, and the chauffeur-driven office car travellers have the highest mean VOTT.