The influence of perceived safety on the acceptance of autonomous demand responsive transportation services in The Netherlands

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Preface

Dear reader,

First and foremost, I would like to thank you for taking time to read my thesis. This project concludes a very educational couple of years of my life as a student of the Tu Delft. After graduating as a bachelor of Science, Business & Innovation at the Vrije Universiteit in Amsterdam, I wanted to further develop my technical skills. This led me to the master program Complex System Engineering & Management (CoSEM). After specializing in transport and logistics and trying to steer as many of my projects as possible into the direction of autonomous vehicles, the perfect opportunity arose at TNO to conduct my master thesis research.

In this preface I would like to exert some words of gratitude towards the people without whom this project would have been impossible. Firstly my supervisors from the TU Delft: Caspar Chorus, Eleonora Papadimitriou and Maarten Kroesen. Caspar, you have been of great help to me during my thesis, both content-related as well as on a personal level. You have supported and motivated me to get to the finish line and become a Master of Science. Eleonora, your sharp analyses and constructive comments always helped me to rethink my steps and improve where them I could. Maarten, thanks a lot for your flexibility and helpful comments during the last weeks of my thesis, without you this wouldn't have been possible.

I would also like to thank my supervisor at TNO, Eleni Charoniti, my other coworkers at SUMS and my fellow interns at TNO. Eleni, we have spent a lot of hours together discussing my progress in our weekly meetings. I would like to thank you for your continuous support, sharing your extensive knowledge on this subject with me and your great eye for detail. I really enjoyed working with you and hopefully our paths will cross again someday, perhaps in a Greek bakery…

Last but not least I would like to thank my family and friends for always supporting me and believing in me. My girlfriend Carlijn for staying positive and motivating me every step along the way. My parents for making my study life possible and for helping me to reflect and develop myself along the way. And many others that offered comic relief and relaxation, which are vital for balancing out hard work.

Furthermore, I am happy to finish this stage of my life as a student and start my professional career. Although I have to be honest and admit that I am still quite doubtful in which direction that may lead…

Kind regards,

Ruben Knipscheer

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List of abbreviations

ADRT = Autonomous Demand Responsive Transport
AI = Artificial Intelligence
AV(s) = Autonomous vehicles
BI = Behavioral Intention
CB = Current Behavior
DCE = Discrete Choice Experiment
DRT = Demand Responsive Transport
EE = Effort expectancy
HM = Hedonic motivation
IDT = Innovation Diffusion Theory
LaaS = Logistics as a Service
LA = Level of Automation
MaaS = Mobility as a Service
MI = Media influence
MNL = MultiNomial Logit
NMM = New Mobility Modeler
PCA = Principal component analysis
PE = Performance Expectancy
PEOU = Perceived Ease Of Use
PS-A = Perceived safety Autonomous DRT
PU = Perceived Usefulness
PT = Public transportation
RUM = Random Utility Maximization
SCE = Stated Choice Experiment
SEM = Structural Equation Model
SHOW = (SHared automation Operating models for Worldwide adoption)
T = Trust
TAM = Technology Acceptance Model
TPB = Theory of Planned Behavior
TNO = Nederlands Organisatie voor Toegepast Natuurwetenschappelijk Onderzoek
UTAUT = Unified Theory of Acceptance and Use of Technology

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Executive summary

One of the major innovations in the coming decades concerning transport could be the introduction of autonomous vehicles (AVs) on public roads. It is anticipated that AV use will provide numerous benefits such as environmental benefits by reducing emissions (Greenblatt & Saxena, 2015), increased vehicle throughput on highways (Talebpour & Mahmassani, 2016) and improved road safety (Fagnant & Kockelman, 2015).

A form of transport that could also see an increase in popularity over the coming years is demand responsive transport (DRT). Demand responsive transport is generally described as an intermediate form of public transport, somewhere between a regular service route that uses small low floor buses and variably routed, highly personalized transport services offered by taxis. Services are routed according to the needs of the customers, generally only stopping where passengers request collection or dropping off. It offers benefits like reducing emissions through more efficient shared trips by passengers, and has the convenience of door-to-door connections without having to pay the premium price for it.

Whereas research is conducted related to the acceptance of DRT services or even autonomous DRT (ADRT) services in rural areas, there seems to be a knowledge gap concerning the acceptance of autonomous DRT services in urban areas of the Netherlands. The research in this master thesis project is conducted in collaboration with TNO as an addition on the new mobility modeler (NMM). TNO aims at using the NMM to provide urban mobility recommendations. The NMM is a model that has been specifically developed to explore the impact of new mobility concepts like connected and automated driving and shared mobility (Snelder et al., 2019). The subject of autonomous DRT services in urban areas could therefore be very interesting, since it adds a new form of transportation to the arsenal of the NMM in a setting that is exemplary to its service area whilst researching an academic knowledge gap. The main research question of this thesis therefore is:

What influences and to what extent the acceptance of autonomous DRT services?

In the current mode choice estimation by the NMM, the attributes of travel time, travel cost and parking time/cost are incorporated in the utility function of the various modes. The limited amount of attributes incorporated in the NMM is for the sake of simplicity and computational intensity. The model has been kept as simple as possible, so mode choice has been based purely on time and cost. Therefore these attributes will also be evaluated and result in the following sub questions:

1. *What is the impact of travel time on autonomous DRT acceptance?*
2. *What is the impact of travel cost on autonomous DRT acceptance?*
3. *What is the impact of parking cost on autonomous DRT acceptance?*

Safety is mentioned as one of the main advantages of AV acceptance in Fagnant et al. (2015), and therefore a deeper analysis of the safety benefits is conducted. The main reason that AV use is expected

to significantly reduce crashes, is because it removes the driver error as a cause for accidents (Fagnant & Kockelman, 2015). Therefore, it could be expected that potential users would regard AVs as a safer alternative compared to regular transport options. But in the case of AV safety, there is a discrepancy between advocated theoretical safety and reported perceived safety. A report from the American automobile association revealed that 78% of American drivers were afraid to ride in AVs (AAA, 2017). The discrepancy between perceived safety and theoretically estimated increased safety of AV is currently under-researched and, therefore, another set of sub questions of this research will be:

4. *What are the determinants of AV safety perception and to what extent do they influence AV safety perception?*

5. *What is the relative impact of perceived AV safety on autonomous DRT acceptance, compared to other variables related to technology acceptance?*

The theoretical framework that was needed to assist in designing the survey and research is based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and findings from the literature review. The behavioral intention to use ADRT and the mode choice of the participants are analyzed to estimate what influences the acceptance of ADRT services. This resulted in the framework as displayed in figure 1.

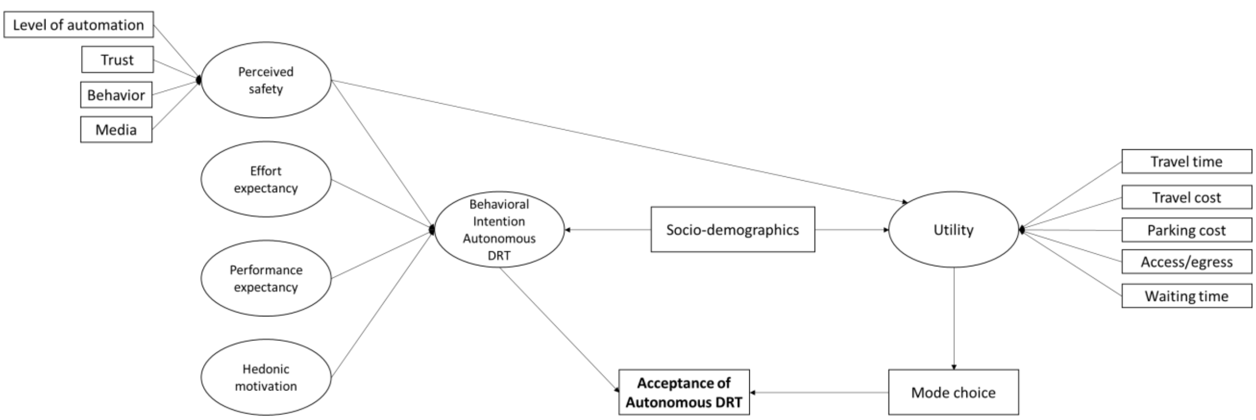


Figure 1 - Conceptual model

To gather respondents for the survey, this research made use of snowball sampling. This is a respondents recruitment technique where the researcher utilises his/her network and encourages the people in it to further spread the survey and recruit respondents. The total number of respondents to the survey amounted to 197. After data cleaning, a total of 105 entries remained for analysis.

A combination of a stated choice experiment and sets of attitudinal questions was presented to the participants. Afterwards the gathered data was analyzed through a MultiNomial Logit (MNL) model and a combination of factor analysis and multiple regression. This generated a series of significant relations among the variables that enabled answering the research questions.

The first result of the analysis relates to the influence of travel time. Travelers seem not to value waiting time, access and aggress time or on board travel time any different, but rather just care about the total travel time of a trip. This is not specifically for ADRT, but that same effect was found for all the different travel modes in the analysis.

Further analysis of the impact of travel cost and travel time revealed that ADRT had the highest value of travel time (VOTT) compared to all of the other alternatives. Meaning that passengers are willing to pay more compared to the other modes in order to reduce their travel time in an ADRT. This was mainly due to the relative magnitude of the travel time estimate of ADRT compared to the other modes. ADRT had the highest parameter estimate of travel time, followed by car and shared car. The lowest parameter estimates belonged to public transportation and shared bicycle.

The differences amongst the modes was less staggering for the estimates of travel cost. Where ADRT scored somewhere along the middle, compared to the highest estimate of shared car and travel cost was the least impactful for bicycle.

Also the influence of parking cost on the acceptance of ADRT is reviewed. Since the ADRT itself does not have parking costs affiliated with a trip made, the only way to review the impact of parking cost is indirect through the effect parking cost has on the travel mode car. When looking into this, it indeed becomes apparent that parking cost significantly influences the decision to choose for the car option. However it has a smaller impact on utility when compared to travel costs. Therefore, acceptance of ADRT services would indeed be impacted by rising or decreased parking costs. However, changes in regular travel costs (as for instance rising gasoline prices), would have a bigger effect on the decreased utility of car and therefore increased utility for ADRT.

Analyzing the results containing data on the determinants of perceived safety, not many significant relations between the variables and perceived safety were identified. Trust and level of automation did portray a significant relation with perceived safety. The higher people indicated that they would feel safe in a level 5 autonomous vehicle, the higher perceived safety of AV's in general. This is a good indication that level of automation influences the perceived safety of autonomous vehicles. A similar relation is identified between trust and perceived safety. The higher the trust in AV technology, the higher the perceived safety of an autonomous vehicle.

The questions related to media influence did not yield a significant relation between media influence and perceived safety. This could indicate that media coverage of news surrounding autonomous vehicles does not influence perceived safety of autonomous vehicles, regardless of it being positive or negative. However, it could also mean that the survey did not contain enough respondents to generate a significant result. Another explanation has to do with a possible bias in the sample. Since a lot of the participants were in the network of TU Delft students, studying CoSEM as well, and employees of the Transport and Logistics department of TNO, it could be that this group of participants is less influenced by reports about AV on the news because it is part of their study and research. So instead of basing their opinion on media coverage, it will rather be shaped by relevant scientific literature or their own research. Also not any of the current behavior questions displayed a significant relation with perceived safety.

From the results of the multiple regression analysis of the effect of the constructs derived from the UTAUT2 theory and perceived safety on behavioral intention to use ADRT, it indeed became apparent that there is a significant relation between perceived safety of AV and behavioral intention to use AV. However compared to the other constructs that were incorporated, perceived safety showed the estimate with the lowest impact. Performance expectancy and effort expectancy were found to be the most important constructs in accepting the technology, followed by hedonic motivation.

Generally speaking, the main determinant influencing the acceptance of ADRT services is travel time. This was uncovered whilst comparing the estimates of travel time and travel cost of the various modes with one another. ADRT also had the highest VOTT of all the alternatives. Once again indicating that cost is somewhat less of an issue for the passengers and that there is a willingness to pay for reduced travel time. Of the constructs derived from the UTAUT2 model, Performance expectancy had the highest impact on acceptance of ADRT. Supporting this claim is that PE1 of the performance expectancy questions was related to reducing travel time.

It was hard to distinguish which of the investigated variables would follow travel time as most important. However, it did become clear that effort expectancy, hedonic motivation, perceived safety, travel cost and absence of parking cost all contribute to the acceptance of ADRT services. Furthermore, the identified significant determinants of perceived safety are trust in AV technology and level of automation of the vehicle.

The constructs performance expectancy and effort expectancy emerged as most impactful on behavioral intention to use ADRT. From the MNL model, it became apparent that ADRT travel time has a higher impact on utility than ADRT travel cost. Therefore policymakers that want to stimulate ADRT acceptance should focus on reducing travel time in an ADRT. This can be done in numerous ways. For instance by assigning dedicated lanes for ADRT vehicles or by having a large fleet of ADRT vehicles.

Another important construct influencing ADRT acceptance is effort expectancy. The easier it is to use the service, the higher the likelihood of acceptance. Since the analysis revealed that ADRT has the highest VOTT amongst the presented travel modes. This means that passengers are willing to pay more to reduce their travel time when driving an ADRT compared to the other modes of transport. Therefore when designing the optimal ADRT service, it doesn't have to be a low budget solution and investing in a high quality service could pay off.

However, this obviously doesn't mean that travel costs associated with the travel service do not influence the acceptance or have no limit. The VOTT obtained in this research for ADRT is €22,57/h, which can be a guideline for the maximal travel cost versus optimal performance in order to obtain the highest acceptance. A less effective way of increasing acceptance of ADRT is raising parking cost for cars. Increasing parking cost can be considered an option when aiming to discourage car use, but it does not seem as the most effective way of increasing ADRT acceptance.

Perceived safety has a significant impact on ADRT acceptance. The determinants of perceived safety are level of automation and trust in the technology. Therefore, solutions to increasing perceived safety of AV's are best to be related to these subjects. It would be advisable to start the introduction of ADRT vehicles with a level 4 autonomous vehicle and increasing trust in the technology would increase acceptance.

This research contributed also to enhancing the validity of TNO’s NMM. By collecting stated choice data, it became possible to estimate parameters based on actual data, instead of making assumptions based on theory. The influence of several attributes of new modes, such as ADRT, can be used in the model, which uses these parameters for further analysis on modal split, traffic intensities etc.

It has also added to the state of the art in academic research by exploring the variables that influence the acceptance of autonomous DRT in urban areas. Amongst travel time and travel costs confirming that perceived safety indeed is a significant parameter in accepting ADRT as a new form of transport. However, the explanation on the determinants of perceived safety fell somewhat short.

1. Introduction

One of the major innovations in the coming decades concerning transport could be the introduction of autonomous vehicles (AVs) on the public road. It is anticipated that AV use will provide numerous benefits such as environmental benefits by reducing emissions (Greenblatt & Saxena, 2015), increased vehicle throughput on highways (Talebpour & Mahmassani, 2016) and improved road safety (Fagnant & Kockelman, 2015). Due to these anticipated benefits, the Dutch government has stated that their aim is to make autonomous driving increasingly important on Dutch roads in the coming years. However, the anticipated benefits as described in all the previously mentioned articles rely on a certain penetration rate of AV technology. Therefore, researching and understanding expected acceptance of AV technology is an important subject for governments, like The Netherlands, in order to effectively design their policies.

Another form of transport that could also see an increase in popularity over the coming years is demand responsive transport (DRT). Demand responsive transport is generally described as an intermediate form of public transport, somewhere between a regular service route that uses small low floor buses and variably routed, highly personalized transport services offered by taxis. Services are routed according to the needs of the customers, generally only stopping where passengers request collection or dropping off (Brake et al., 2004). It offers benefits like reducing emissions through more efficient shared trips by passengers, and has the convenience of door-to-door connections without having to pay the premium price for it. This research will be focused on a combination of the two previously mentioned technologies: Autonomous demand responsive transport (ADRT).

This research will be conducted in collaboration with TNO for the EU SHOW project (https://show-project.eu/), which TNO is currently involved in. SHOW (SHared automation Operating models for Worldwide adoption) aims to support the migration path towards effective and persuasive sustainable urban transport, through technical solutions, business models and priority scenarios for impact assessment, by deploying shared, connected, cooperative, electrified fleets of autonomous vehicles in coordinated Public Transport (PT), Demand Responsive Transport (DRT), Mobility as a Service (MaaS) and Logistics as a Service (LaaS) operational chains in real-life urban demonstrations in 5 Mega, 6 Satellite and 3 Follower Pilots taking place in 20 cities across Europe. The contribution of TNO in this project is to develop holistic simulation methods and tools for CCAV impact assessment and prospective studies and to provide specific recommendations of urban mobility modelling practices, models and tools.

TNO aims at using the New Mobility Modeler (NMM) to provide urban mobility recommendations. The NMM is a model that has been specifically developed to explore the impact of new mobility concepts like connected and automated driving and shared mobility (Snelder et al., 2019). It is an explorative iterative model that uses a multinomial logit model (MNL) for mode choice and a traffic assignment model to assess traffic impacts. One of the goals of this research is to improve the NMM. An important step is to improve the current assessment on how many people will use AVs once they are available. In the NMM so far, the estimations are not based on collected data and thus can be improved. One of the recommendations in the paper by Snelder et al. (2019) is to research the uncertainties with respect to user acceptance of automated vehicles, by carrying out stated preference research. This research aims at doing so, by exploring several attributes influencing the expected acceptance of autonomous DRT services in the Netherlands through a stated choice experiment (SCE).

This subject fits the CoSEM program perfectly, since CoSEM thesis research is characterized by approaching socio-technical problems that cover values originating from the public and private domain. The introduction of ADRT and acceptance of the technology is a perfect example of a subject that is a combination of understanding technological advancement through social study. Also, it has a clear design component as the design of a stated choice experiment and discrete choice model is incorporated in the research.

2. Academic knowledge gap & research questions

The main goal of this research is to identify the attributes influencing autonomous DRT services acceptance in urban areas of the Netherlands and their relative impact on acceptance. Simultaneously the research aims at improving the validity of TNO's NMM. In particular, the mode choice estimation model of the NMM will be reviewed and improved. Currently, the mode choice estimation is done through a multinomial logit model with utility functions per mode containing attributes like travel time, travel cost and parking time/cost, as well as an age dummy constant and mode specific constant (Snelder et al., 2019). The estimation is based on data gathered from literature study. To attain these research goals a stated choice experiment will be conducted and the main research question will be:

What influences and to what extent the acceptance of autonomous DRT services?

In the current mode choice estimation by the NMM, the attributes of travel time, travel cost and parking time/cost are incorporated in the utility function of the mode. The limited amount of attributes incorporated in the NMM is for the sake of simplicity and computational intensity. The model has been kept as simple as possible, so mode choice has been based purely on time and cost. Therefore, these attributes will also be evaluated in the stated choice experiment and result in the following sub questions:

1. *What is the impact of travel time on autonomous DRT acceptance?*
2. *What is the impact of travel cost on autonomous DRT acceptance?*
3. *What is the impact of parking cost on autonomous DRT acceptance?*

In the previous section, some of the expected benefits from implementing AVs on the public road have been presented. Safety is mentioned as one of the main advantages of AV acceptance in Fagnant et al. (2015), and therefore a deeper analysis of the safety benefits is conducted. The main reason that AV use is expected to significantly reduce crashes is because it is removing driver error as a cause for accidents (Fagnant & Kockelman, 2015). Fagnant et al. (2015) state that driver error is believed to be the main reason in over 90% of all crashes in the United states of America. Removing that safety hazard from the equation by replacing it with AV artificial intelligence (AI), should result in a dramatic drop in crashes. Of course the AV AI cannot be considered flawless, but at least it is insensitive to alcohol, distraction, drug involvement and/or fatigue which together are responsible for at least 40% of North-American crashes. The other human error induced crashes are due to speeding, aggressive driving, overcompensation, inexperience, slow reaction times, inattention and various other driver shortcomings. Also, data from field tests with AVs by industry giant Google indicate that their AV AI indeed outperforms the average driver when it comes to a safe driving style (Simonite, 2013).

Taking this into account, it could be expected that potential users therefore would regard AVs as a safer alternative compared to regular transport options. But in the case of AV safety there is a discrepancy between advocated theoretical safety and reported perceived safety. A report from the American automobile association revealed that 78% of American drivers were afraid to ride in AVs (AAA, 2017). On top of that, fatalities caused by AVs receive more negative weight than fatalities caused by human drivers in conventional vehicles (Huang et al., 2020). Meaning that potential users do not only consider AVs to be more dangerous, but also are less forgiving to their (theoretically) fewer mistakes. However, as Huang et al. state in their paper, the overweighting of fatalities caused by AVs is partly explained by a reference level effect. Meaning that due to the currently extremely low number of AV induced fatal accidents, any increasing number appears to be relatively high, even though the absolute number for conventional vehicle fatalities might be a multitude higher. The discrepancy between perceived safety and theoretically estimated increased safety of AV currently is under-researched and therefore another sub question of this research will be:

4. *What are the determinants of AV safety perception and to what extent do they influence AV safety perception?*

One of the options to decrease that negative perception on AV safety could be to increase the number of AV trips. However, this solution is prone to what one might call an attitude-behavior paradox. In Kroesen et al., 2017 it becomes apparent that travel behavior influences the user's attitude towards a specific travel mode, more so than vice versa. Since AVs are currently not publicly available, behavior (or use of AV's) cannot change the attitude directly. It can however indirectly influence the attitude towards AV safety. Since users are forced to use conventional vehicles now, their attitude towards those travel modes will be influenced by their use of that specific travel mode. In the paper by Kroesen et al it is also argued that people are more likely to adjust their attitudes (instead of their behavior) when faced with dissonance. This refers to the social study of cognitive dissonance. Given that AV driving is theoretically safer, this implies that human driving is (more) dangerous. In turn that can be considered dissonance between the human driver's conventional vehicle behavior and the cognition that "human driving is dangerous". As stated, users are more likely to change their attitude and on top of that there is no opportunity to change behavior to AV use. Therefore, changing cognition to "AV driving is dangerous" or "human driving is not that dangerous" could be considered a logical option.

Another interesting phenomenon to investigate in relation to AV safety perception is the discovered relation between the formation of attitudes towards bicycling and crashes and other safety-related incidents (Lee et al., 2015). In the research by Lee et al, it is discovered that incidents experienced by other bicyclists were far more traumatic and damaging to attitudes toward bicycling than those experienced firsthand, at least for infrequent bicyclists. This relation provides two areas of interest when looking at the AV safety perception. Firstly, a direct relation. Since AV use currently is not publicly available, all information regarding AV accidents is received secondhand and therefore can be considered harmful to the attitude towards AV. The role of media coverage on AV accidents could therefore be of a significant influence. More so than media coverage of regular accidents, since users are more likely to have been involved in accidents there. It is also interesting to see how direct or indirect involvement in accidents with rivalling travel modes (like human driven car or PT) influences the attitude towards AV. Because it could be argued that the first, but especially negative secondhand experience with rivalling travel modes would increase the likelihood of adopting a theoretically safer travel alternative like AV. A similar effect is observed by Elias and Shiftan, where the perception of the risk of being involved in road crashes and fatalistic beliefs exerts a positive effect on travel behavior – namely, a willingness to use PT (Elias & Shiftan, 2012).

What is also considered a major determinant in the acceptance of autonomous vehicles is trust (Choi & Ji, 2015). In their research Choi & Ji found that trust has a direct effect on intention to use autonomous vehicles as well as an indirect effect through perceived risk. Perceived risk here is described as the perceived uncertainty in a given situation. As this closely relates to perceived safety of an AV, it is expected that trust in AV will indeed also be one of its important determinants.

After identifying the main determinants for perceived safety and their relative influence on the formation of this perceived safety, the impact of perceived safety influencing the acceptance of autonomous DRT services will be investigated as well. Therefore, the following sub question will be incorporated in the research as well:

5. *What is the relative impact of perceived AV safety on autonomous DRT acceptance, compared to other variables related to technology acceptance?*

3. Conceptual model

In the previous section, a relevant academic knowledge gap concerning autonomous DRT acceptance has been identified. This is done through literature review and results in a set of research questions that satisfy both the interests of TNO and Delft university. To structure the design of the experiment a theoretical framework that visualizes the relation between the attributes of interest and the acceptance of autonomous DRT services will be created based on literature research.

A review of studies related to the studied subject revealed that important theories which should be considered when constructing the theoretical framework are the Technology Acceptance Model (TAM) by Davis (Davis, 1989) and the Innovation Diffusion Theory (IDT) by Rogers (Rogers, 1983). The TAM proposes that the acceptance of new technology is mainly influenced by the variables perceived usefulness (PU) and perceived ease of use (PEOU). The IDT states that there are five main factors that influence the adoption of an innovation: relative advantage, compatibility, complexity, triability and observability. These factors all have a different effect on the 5 identified groups of adaptors: Innovators, early adopters, early majority, late majority, and laggards. These theories have been applied successfully in several AV acceptance studies (Yuen, Cai, Qi & Wang, 2020) (Müller, 2019) (Yuen, Wong, Ma & Wang, 2020). A behavioral model that combines both these models, and a total of 8 relevant theories from various disciplines like the Theory of Planned Behavior (TPB) and the Diffusion of Innovation (DoI), is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Thong & Xu, 2012). The incorporation of the three new constructs hedonic motivation, price value, and habit led to the creation of the UTAUT2 model. Since its introduction in 2012, the UTAUT2 model has been adopted widely amongst researchers studying user acceptance and its predictive value has been proven time and time again (Tamilmani, Rana, Wamba & Dwivedi, 2021). Therefore, UTAUT2 is seen as a good starting point in identifying useful research to further build upon for this research.

In search of relevant literature relating to AV acceptance that incorporates UTAUT2 in their theoretical framework, the paper of Curtale et al. (2022) presents a study that seeks to explore a similar knowledge gap as this research does (Curtale, Liao & Rebalski, 2022). In their paper Curtale et al. (2022) investigate the behavioral intention to use autonomous electrical car sharing using psychological constructs partially from UTAUT2 and an additional one expressing safety concern. This resulted in the conceptual model as shown in figure 1.

This theoretical framework contains a set of psychological constructs and their expected relation. A psychological construct can be described as a label for a cluster of covarying indicators. An example of a psychological construct could be intelligence. Since intelligence cannot be measured directly, variables that are expected to relate to intelligence (or indicators), as for instance the speed of a person to resolve a mathematical problem, are used to construct a quantitative value for the psychological construct. A well-known example related to measuring the psychological construct intelligence is an IQ test.

In the conceptual model presented in figure 1, the constructs performance expectancy, effort expectancy, social influence, hedonic motivation, safety concern and behavioral intention are mentioned.

Performance expectancy is the degree to which a travel mode will provide benefits to a passenger using that travel mode. Effort expectancy is degree of ease associated with using the travel mode. Hedonic motivation is the fun or pleasure derived from using a technology. Social influence is the extent to which passengers believe influential individuals in the passengers social environment feel that they should use this travel mode. Whereas behavioral intention relates to the willingness or intention of a passenger to use a certain travel mode.

Performance expectancy, effort expectancy, and social influence are considered the predictors of behavioral intention to use electric car sharing because they expected high reliability of these factors for an already diffused technology and service. Hedonic motivation is considered separately for both electrical car sharing and autonomous electrical car sharing, because of strong evidence of its relative importance in various studies. Safety concern is only considered for autonomous electrical car sharing, since it is expected that it influences AV acceptance but not human driven electrical car sharing services.

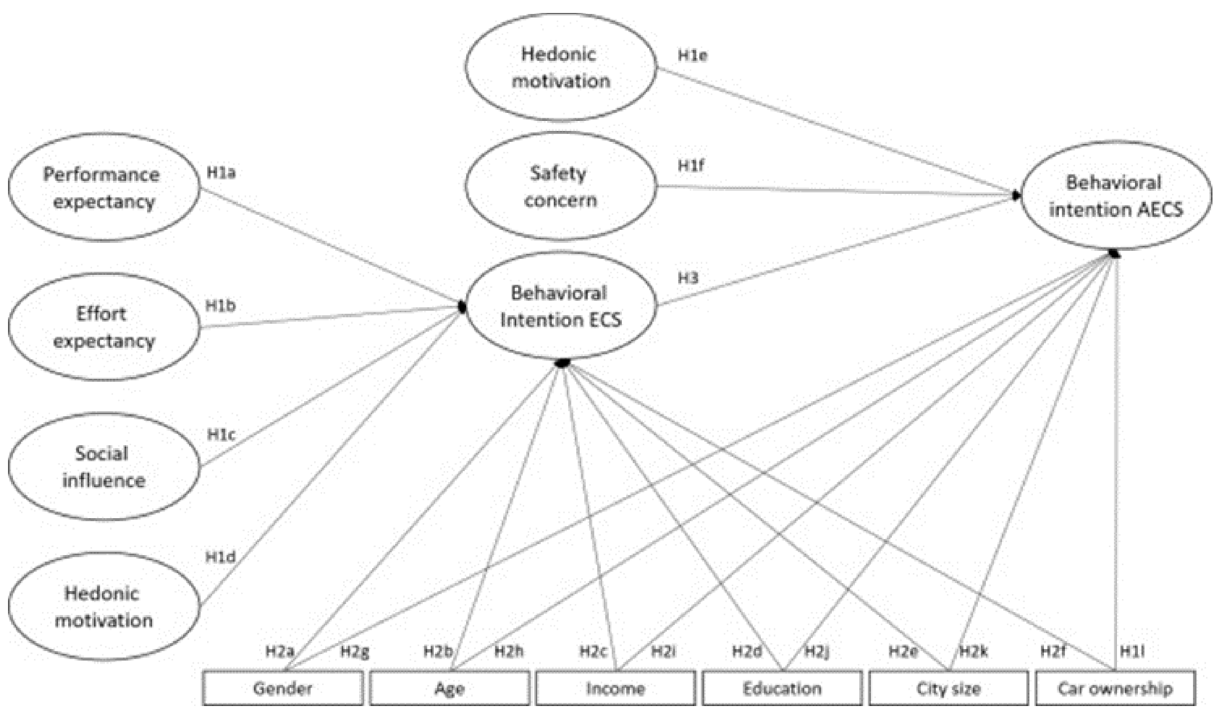


Figure 2 - Conceptual model Curtale, Liao & Rebalski (2022)

The conceptual model presented by Curtale et al. (2022) can therefore, form a solid basis for the conceptual model of this research, since it provides a well-tested behavioral model to predict user acceptance of autonomous vehicle services and incorporates safety concerns as well. Also the experiment was partly conducted in the Netherlands and therefore could help in the determination whether the sample of this research can be considered representative. The recruitment process of respondents in the research by Curtale et al. (2022) was performed by a professional panel for market research (Panelclix), to ensure representativeness of their Dutch sample. The sample in their research was indeed found to be representative of the Dutch population, with a slightly above average level of education and income.

Because of similarities in research subject and research area the conceptual model of Curtale, Liao & Rebalski is a good starting point for the conceptual model of this research. However it only partly covers the main and sub-questions of this research as well as containing the segment of social influence that is considered out of scope for this research. This is partly because of the limited relevance of the questions relating to the travel mode autonomous DRT. The questions concerning social influence used in the survey are based on the idea that electric car sharing is a widely known concept. Therefore social influence of the participants network is possible and/or likely. However, due to the limited awareness of autonomous DRT as a mobility option, the question about social influence wouldn't make a lot of sense. Social influence as a construct therefore is omitted from the theoretical framework for this research.

The theoretical framework of Curtale et al (2022) mainly conceptualises sub question 5 of this research "What is the relative impact of perceived AV safety on autonomous DRT acceptance, compared to other variables related to technology acceptance?". Therefore several constructs need to be added to the conceptual model in order to capture the specific research needs of this study. One of the elements that need to be featured in the adapted conceptual model is sub question 4. Sub question 4 seeks to uncover the determinants of perceived safety and, as is explained in chapter 2, the expected possible determinants are: Current travel behavior, media influence, trust in AV and level of automation.

However in order to satisfy all the research goals of this study another addition to the conceptual model needs to be made. To comment on the expected acceptance of autonomous DRT it is assumed that the process of choosing autonomous DRT as a travel mode is part of a set of attributes in a utilitarian decision making process. The utility of a travel mode can be described as the absolute value measurement made by people in travel decisions based on a set of attributes, as for instance travel time or cost. It commonly believed that travelers follow the principle of maximizing utility in the process of travel behavior selection (Liu, Chen, Wu & Ye, 2019). The attributes incorporated in this research are therefore expected to influence the utility of a travel mode and therefore impacting the mode choice of a traveler. The incorporated attributes in this study are: Travel time, travel cost, parking cost, access/egress time and waiting time. Perceived safety also will be tested as part of a utility function for ADRT. With these additions, sub questions 1,2 & 3 also have been incorporated in the conceptual model. Access/egress time and waiting time also have been added to the model. A discrete choice experiment by Kolorava Steck & Bahamonde-Birke on user preferences toward currently available and future available modes of transportation also was an inspiration for addition of these constructs (Kolarova, Steck & Bahamonde-Birke, 2019). The research done by Kolorova et al. (2019) used similar transport modes as incorporated in this experiment and determined that those attributes were of significant importance to incorporate in the choice task. The most important reason to include them is to make the choice decision as close to a real situation as possible.

In summary, this research will incorporate the constructs perceived safety, effort expectancy, performance expectancy and hedonic motivation and investigate their impact on behavioral intention to use ADRT. The effect of the attributes travel time, access/egress time, waiting time, travel cost and parking cost on utility and mode choice are studied as well. Perceived safety will also be investigated as a possible significant variable in the utility function of ADRT. The behavioral intention to use ADRT and the mode choice of the participants are then analyzed to estimate what influences the acceptance of ADRT services. This resulted in the final conceptual model for this research as depicted in figure 2.

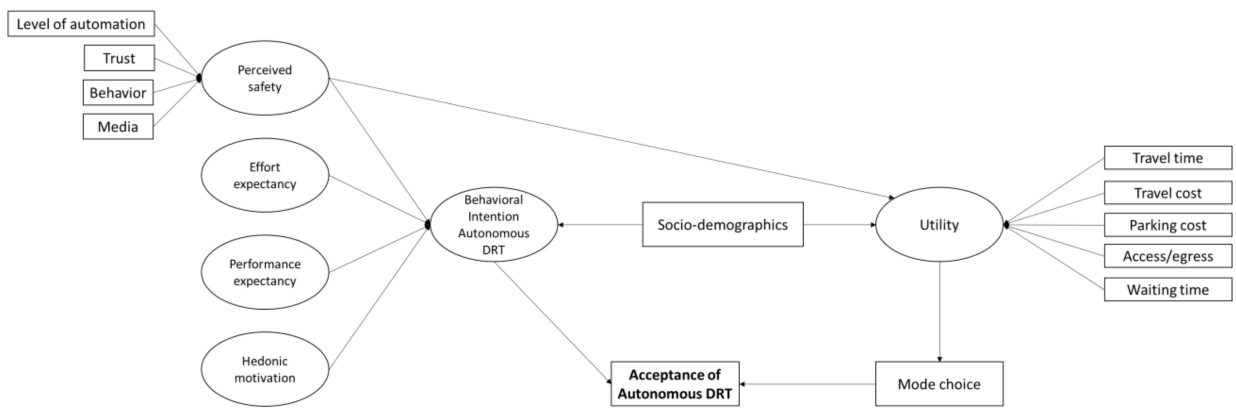


Figure 3 - Conceptual model

4. Method & survey

Research Method and methods of analysis

Stated choice experiment

To answer the research questions of this thesis project a method of gathering information about travelers choice behavior must be chosen. For this research the method of a discrete choice experiment was considered to be the best option. In a discrete choice experiment the participant is presented with several discrete alternatives. In this particular research that will consist of various travel modes that each contain attributes expected to influence the choice of the participant. Discrete choice modelling is considered to be an excellent method of capturing travelers sensitivities to attributes of various travel modes without directly asking participants about them (Train, 2003).

The underlying theory of discrete choice modeling is random utility maximization (RUM). The RUM theory states that a person will try to maximize expected utility. The utility function U_i of the RUM theory is presented in the function below (1):

$U_i = \Sigma_n^m \beta_m * x_{im} + \varepsilon_i$ (1)

Where β_m is the weight participants attribute to mode characteristic m, multiplied by the performance x_{im} of transport mode i on that characteristic. The overall expected utility of an alternative is calculated by the summation Σ_n^m over all the utilities per mode characteristic. ε_i is the noise added to the utility representing all uncaptured utility in the research.

In a discrete choice experiment, researchers can choose to present the participants with either revealed preference or stated choice preference. In which revealed choice asks participants to indicate which choice they have made in the past in a certain scenario and stated preference asking the participant to consider which choice they would make in a hypothetical future situation. Since autonomous DRT is currently an unavailable mode of transport, the only possible research method is a stated choice experiment.

Multinomial logit model

After gathering the data through the stated choice experiment, the data must be analyzed in order to interpret it. One of the most frequently used models to analyze mode choice probabilities of travelers is the Multinomial Logit (MNL) model (Train, 2003). In formula 2 the underlying formula related to the MNL model is presented:

$$P_i = \frac{e^{u_i}}{\Sigma_{J=1}^{J} e^{u_j}} \text{ (2)}$$

U_i is the derived utility for an alternative chosen by the decision-maker i. Consequently, U_i is set out against the sum of utilities, of all alternatives in the decision-making process. P_i is the probability of the decision-maker for choosing alternative i instead of alternative j.

After running a model, the goodness of fit of the data with the model must be evaluated. To do so the log likelihood and rho squared values in the results of the model are important to observe. The log likelihood can be described as the likelihood of a model fitting a data set according to a logarithmic formula. In general, the higher the log likelihood, the better the goodness of fit of a model. However this can only be used to compare several models of the same data with one another. For a more general estimation of the goodness of fit, the rho squared value is important. The rho squared value is the percentage of the response variable variation that is explained by a linear model. It always represents a value between 0 and 1. In general a rho squared value ranging between 0.2 and 0.4 represents a good fit of the model with the data (McFadden, 1977).

Factor analysis

In the survey, multiple questions refer to the same construct. This will result in a large number of variables that need to be correlated with the variables of interest. In order to measure the underlying psychological constructs of the variables, factor analysis can be applied extracting the maximum common variance from the relevant variables and combining them in a common score (a factor).

In this research, to identify whether variables can be combined into a common factor, a principle component analysis is conducted. Principal component analysis (PCA) is a technique for reducing the dimensionality of datasets, increasing interpretability but at the same time minimizing information loss. It does so by creating new uncorrelated variables that successively maximize variance (Jolliffe & Cadima, 2016).

When performing a PCA, several rotation methods can be selected. In the analysis for this research, direct oblimin rotation has been selected. This is mainly due to the expected correlation amongst the factors and direct oblimin rotation allows factors to correlate.

Afterwards, either linear regression or multiple regression analysis was applied in order to identify the relationship between the factors. Regression analysis is a statistical technique for estimating the relationship among variables which have linear relation. The goal of univariate regression is to analyze the relationship between a dependent variable and one independent variable and formulates the linear relation equation between dependent and independent variable. Regression models with one dependent variable and more than one independent variables are called multilinear regression (Uyanık & Güler, 2013).

SCE design

As is briefly touched upon before, the research method of this project consists of conducting a stated choice experiment in combination with a range of attitudinal questions. The attitudinal questions are presented to the participants in order to estimate the influence of the psychological construct "Behavioral intention to use autonomous DRT". Attributes like travel time, travel cost, parking time, access/egress time and waiting time are presented in the SCE in order to estimate their effect on utility and ultimately acceptance of autonomous DRT. Also this research aims to acquire a deeper understanding of the determinants of "perceived safety of AV". In this chapter the survey design will be presented, based on the logic of the previously presented conceptual model. Data relating to the various constructs in the conceptual model are acquired through "attitudinal questions" and a "stated choice experiment". In this chapter the design of the survey will be presented as well as the rationale behind it.

The survey that will be presented to the participants is designed in Qualtrics. Within the survey participants will first read the introduction as presented in appendix A. This introductory text informs the user on the incorporated travel modes presented in the choice experiment, so no ambiguity can exist around their function. Since participants are confronted with travel concepts that are not yet available, this is a very important step in the process. Under explanation, or unclear explanation, of these concepts could result in unreliable results due to misunderstanding the function of the new travel modes. After reading the introduction, the participants will engage in a stated choice experiment and afterwards the set of attitudinal questions will be presented. The order of the two data gathering methods is not coincidental. The attitudinal questions are presented to the participants after the choice experiment to prevent possible influence of these questions on the choices made in the experiment. The scenario that participants are confronted with, which they will need to make a mode choice on, is:

You have an appointment in a city. At the moment of departure you are already in that same city and the distance to your appointment is 5 kilometers. You will travel to this destination and will stay on that location for approximately 2 hours. After the appointment you will leave this location and resume your day.

Considering the proposed situation the participants are presented with several discrete alternatives. In this particular research that consists of various travel modes each containing attributes expected to influence the choice of the participant. By offering the participants these discrete choices, the choice made by the participants can be statistically correlated to the attributes of the travel mode or the attributes of the participant.

Since this research specifically focuses on the acceptance of autonomous DRT, one of the travel modes that will be incorporated in the set of alternatives is autonomous DRT. When designing a discrete choice experiment, the researcher can generally make use of either revealed preference data or stated preference data. Revealed preference data contains information about choices made in real life by the participants. Although revealed preference data provides reliable choice data, it lacks the ability to investigate new or unavailable travel modes. Stated preference data is collected through presenting participants with a hypothetical scenario and asking them to make a choice considering a set of alternatives. Even though the choices made are less reliable than those gathered by using the revealed preference method (because of the hypothetical nature of the stated preference data), it does offer the possibility to research future or currently unavailable travel modes. Since autonomous DRT is a travel mode that is currently unavailable, the experiment will rely on stated choice by the participants.

To be able to compare the relative importance of the attributes of autonomous DRT acceptance compared to other travel modes, several alternative travel modes need to be incorporated in the SCE as well. Travel modes that will be incorporated in the set of alternatives are dependent on the currently available travel modes incorporated in the NMM. Similarity in this choice set will ensure that the results gathered by the experiment are compatible with the NMM mode choice estimation model. The travel mode alternatives that currently are incorporated in the NMM are car driver (level 0/1/2), car passenger, train, bus/tram/metro, bicycle, walking, trucks (level 0/1/2), automated private car (level 3/4 or 5), automated taxi, automated shared taxi, automated shared van and shared car (Snelder et al., 2019).

In selecting which modes to incorporate as the choice experiment alternatives it is important to have a good balance in available options. When there are too many options the choice becomes too difficult, but when there are too few options the experiment won't provide the wanted insights. The focus of the NMM is on inner city travel, as is the situation presented to the participants, and therefore the travel modes that are incorporated in this research are the ones that fit this travel need best. The alternatives that will be included in the experiment are: Car, Public transport (bus/tram/metro), shared bicycle, shared car and autonomous DRT. The attributes incorporated in this research are: Travel time, travel cost, parking cost, access/egress time and waiting time. The complete set of alternatives and their attributes are presented in table 1. The stated choice experiment was designed in Ngene. Ngene is a software tool to generate experimental designs for stated choice surveys. The code used to generate the design can be found in Appendix A. An explanation on the levels of the attributes is given in the next paragraphs.

	Car	*Public transport (Bus/tram/metro)*	*Shared Bicycle*	*Shared car*	*Autonomous DRT*
Travel time	12/15/20 min	14/18/24 min	18/24/30 min	12/15/20 min	14/18/24 min
Travel cost	€2,50/€3,20/€4,30	€1,90/€2,40/€3,20	€1,90/€2,40/€3,20	€3,40/€4,30/€5,80	€2,50/€3,20/€4,30

Parking cost	€4/€5/€7	None	None	None	None
Access/egress time	2/5/10 min	2/5/10 min	2/5/10 min	None	None
Waiting time	None	2/5/10 min	None	None	2/5/10 min

Table 1 – choice alternatives and attributes for the stated choice experiment

The levels of the attributes are based on a research performed by Kolarova, Steck & Bahamonde-Birke that contained very similar alternatives as this study (Kolarova, Steck & Bahamonde-Birke, 2019). In their study the participants were asked for reference trips in a revealed preference part of the study and the entered values were redistributed to the participants in the stated choice part, only the original value was altered with -30%, -10% and +20% of the reference levels. The levels of waiting time and access/egress time were varied between 2/5/10 minutes.

Participants in this research will not provide a reference trip, but are presented with the previously mentioned scenario. This scenario describes a travel distance of 5 kilometers in a city and therefore the reference time/cost is based on that situation and the levels presented to the participants are calculated according to that reference level. The calculated reference level for travel cost and parking cost will be used as the lower bound, with the other values calculated accordingly. This was done, since the calculated prices for some alternatives were relatively low. This negatively influenced the total difference between the lower and upper bounds and that limits the choice variance for the participant. Increasing the total difference of the attribute levels ensures that participants face a more diverse choice task, therefore the attributes gain a higher exploratory value in the final analysis. However it is important to always bear in mind that a good balance between reality and choice variance is achieved.

To calculate travel time, the average speed per mode in the city of Amsterdam is used. For cars the average inner city speed is estimated at 18 km/h and for bicycle and public transportation the average speed is 15 km/h (Gemeente Amsterdam Dienst infrastructuur en vervoer, 2010). The calculated travel times are rounded to whole minutes in favor of the clarity of the presented choices.

The travel cost per mode is calculated by using the estimated cost per kilometer in the city of Amsterdam for each mode. The average price per kilometer for a medium sized car is €0,50 (Nibud, 2022). This is based on a gas price per litre of €1,81 and therefore might be quite low compared to current prices. However, because the current rise in gas prices is due to the extraordinary tragic events in Ukraine, this research assumes the prices will drop somewhat in the near future in hope of de-escalation in the Russian-Ukraine conflict. For the travel costs, in favor of the clarity of the choice task the levels are rounded. In the paper of Kolarova, Steck & Bahamonde-Birke the cost for autonomous shared taxi is considered to be similar to that of a car. Therefore that same logic will be applied in this research. Public transportation in Amsterdam has a starting price of €1,01 and costs €0,179 per kilometer (GVB, 2022). For 5 kilometers, the reference level price of public transportation therefore is €1,91. For shared car the prices on the website of Share Now are used, which are €0,28 per minute (Share Now, 2022).

In this experiment €2,00 an hour is used for the parking cost calculation. In the presented situation, the participants stay at their destination for 2 hours, so the reference level is €4 in parking cost.

A pilot study was conducted prior to launching the final survey. The reason to perform a pilot study prior to the final survey was two-fold. Firstly, to gather information about the priors that can be used in the efficient design in Ngene. A prior is a best guess of the true parameter values. Priors are important in efficient designs since they improve the quality of the stated choice experiment design. Secondly, to check for dominant alternatives and inconsistencies or unclarities in general in the survey. A dominant alternative is an alternative that outperforms the other alternatives on all the attributes and therefore is chosen a disproportionate amount compared to other alternatives.

In the pilot survey a total of 11 respondents participated and provided feedback about the presented choice tasks. In the total of 99 choice tasks presented, the bicycle was chosen 59 times. Therefore making up 59,8% of choices made overall. The alternatives car and public transportation were chosen 4 and 5 times respectively out of 99 times total. Autonomous DRT and shared car were chosen a bit more often, with respective values of 10 and 21.

The pilot revealed that the bicycle was too much of a dominant alternative within the dataset. This was resolved before the final survey was released, because having a dominant alternative will result in a dataset that contains too little information about what attributes influence the actual choice of the participant. The feedback of the pilot participants revealed that the reason to choose for bicycle very often was the lack of travel cost for this alternative, combined with travel times being relatively comparable to the other modes. To overcome the problem of bicycle being too dominant of an alternative, in the final survey design the travel mode bicycle was replaced by the travel mode “shared bicycle”. This added the attributes of travel cost and access and egress time to the alternative. The travel cost of shared bicycle was estimated to be similar to the cost of public transportation.

Attitudinal questions

After completion of the stated choice experiment, the participants will also be presented a set of attitudinal statements. The agreement of the participants with the presented statements is measured through a five point Likert scale ranging from 1 “totally disagree” to 5 “Totally agree”. In table 2 the constructs and their corresponding attitudinal questions are presented. These attitudinal statements are derived from the research of Curtale, Liao & Rebalski. The constructs and statements are adapted versions of previous studies applying UTAUT and UTAUT2 (Curtale, Liao & Rebalski, 2022) (Fleury, Tom, Jamet & Colas-Maheux, 2017) (Madigan, Louw, Wilbrink, Schieben & Merat, 2017) (Tran, Zhao, Diop & Song, 2019) (Venkatesh, Morris, Davis & Davis, 2003) (Venkatesh, Thong & Xu, 2012).

Constructs	*Source*
Performance expectancy (PE) PE1 I assume that autonomous DRT will help me save travel time. PE2 I assume that autonomous DRT will help me transfer to other transport modes. PE3 I assume that autonomous DRT will enhance my engagement in activities at the destinations. Effort expectancy (EE) EE1 I assume it is easy to learn how to use autonomous DRT. EE2 I assume it is easy to become skillful at ordering autonomous DRT. EE3 I assume a clear and understandable interaction with the autonomous DRT vehicle.	(Curtale, Liao & Rebalski, 2022) (Fleury, Tom, Jamet & Colas-Maheux, 2017) (Madigan, Louw, Wilbrink, Schieben & Merat, 2017) (Tran, Zhao, Diop & Song, 2019) (Venkatesh, Morris, Davis & Davis, 2003) (Venkatesh, Thong & Xu, 2012).

Hedonic motivation (HM)	
HM1 I think using autonomous DRT is fun.	
HM2 I think using autonomous DRT is entertaining.	
HM3 I think using autonomous DRT is enjoyable.	
Behavioral intention (BI)	
BI1 I intend to use autonomous DRT occasionally.	
BI2 I intend to use autonomous DRT for my regular trips.	
BI3 I would encourage my friends/colleagues to use autonomous DRT.	
Perceived safety Autonomous DRT (PS-A)	
PS-A1 I think Autonomous DRT is not ready for public use in urban mobility.	
PS-A2 I think Autonomous DRT is a threat to pedestrians	
PS-A3 I think Autonomous DRT is a threat to other vehicles	
PS-A4 I think Autonomous DRT is not secure enough for travelers.	

Table 2 – Adapted constructs derived from Curtale, Liao & Rebalski, 2022

This research also incorporates another set of attitudinal statements to gain a broader understanding of the determinants of perceived safety of autonomous vehicles. The relevant constructs and their corresponding attitudinal statements are presented in table 3.

Constructs	*Source*
Current Behavior (CB) CB1 A travel mode I regularly use is Car CB2 A travel mode I regularly use is Public transportation CB3 A travel mode I regularly use is Bicycle CB4 A travel mode I regularly use is Shared Car	*Constructed for this research*
Trust (T) T1 Autonomous vehicles are dependable T2 Autonomous vehicles are reliable T3 Overall, I can trust autonomous vehicles	*(Choi & Ji, 2015)*
Level of Automation (LA) LA1 I feel safe as a passenger in a human driven car LA2 I would feel safe as a passenger in an autonomous vehicle with a human driver that can take over control LA3 I would feel safe as a passenger in a fully autonomous vehicle without a human driver	*Constructed for this research*

Media Influence (MI)	*Constructed for this research*
MI1 When I read/hear about autonomous vehicles in the news its usually about accidents	
MI2 When I read/hear about autonomous vehicles in the news its usually about the benefits of the technology	
MI3 I am affected by the news I read/hear about autonomous vehicles	

Table 3 – Attitudinal statements exploring the determinants of AV perceived safety

Finally a set of sociodemographic questions will be presented to the participants. These are similar to those used in the research by Curtale, Liao & Rebalski.

Subject	*Answers*
Gender	Male/female/Non-binary third gender/prefer not to say
Age	*enter number*
Education	Elementary school High school MBO 2,3 or 4 HBO or WO bachelor HBO or WO master PhD Unknown

Income	I prefer not to tell Lower than 1500 1500-2500 2500-3500 3500-4500 Higher than 4500
Car ownership	Yes/no
Possession of drivers licence	Yes/no
Dutch residency	Yes/no

Table 4 – Sociodemographic questions

Data collection & cleaning

To gather respondents for the survey, this research made use of snowball sampling. This is a respondents recruitment technique where the researcher utilises his/her network and encourages the people in it to further spread the survey and recruit respondents. An unintended negative effect of this technique is a generated unrepresentative sample. Since it is highly unlikely that the network of the researcher consists of a group of people that accurately reflects the demographics of Dutch society. Furthermore, utilising TNO's network and that of researchers in the field of smart mobility might be prone to a certain bias amongst respondents of the survey. Therefore it is important to compare the results of this survey to the one of Curtale et al. (2022) in order to determine whether the sample is representative or how it differs from a representative sample and what this could possibly mean for interpretation of results.

The total number of respondents to the survey amounted to 197. However, not all of the survey entries were useful for analysis. To be eligible for analysis the survey entries have to meet a set of criteria. First of all, since the research is focused on the acceptance of autonomous DRT in The Netherlands, the respondents had to be residents of The Netherlands. Also, it is important that all of the 9 choice tasks were completed and that there was sufficient variance in the mode choices. If there is no variance in the mode choices, this is known as non-trading behavior. There are several reasons why a respondent might be exerting non-trading behavior. This could be due to a very strong preference for one of the offered travel alternatives or boredom during the survey. Whatever the origin of this behavior may be, a lack of variance in the answers could pose troubles in the analysis of the data and therefore these responses were omitted from the final data set. When selecting whether the respondents live in The Netherlands and finished the survey a total of 80 responses were removed. An additional 12 responses were omitted because of the lack of trading behavior. Therefore selecting on these characteristics resulted in a final dataset consisting of 105 respondents.

5. Survey data

Factor analysis

The first step in analyzing the data is to analyze whether the questions in the survey related to the psychological constructs can be combined into a mean for their respective construct, by conducting a factor analysis as described in the method.

Factor analysis perceived safety and behavioral intention

The first construct to investigate is perceived safety. As perceived safety is a big part of this research it is most logical to start there. Therefore conducting a principal component analysis of perceived safety of AV and behavioral intention to use AV was the first step in this phase of the analysis. In table 5 the correlation matrix of PS-A1 until PS-A4, which relate to the construct perceived safety, and BI1 until BI3, which relate to the construct behavioral intention to use AV, are presented.

Correlations

	PS-A1	**PS-A2**	**PS-A3**	**PS-A4**	**BI1**	**BI2**	**BI3**
PS-A1 I think Autonomous DRT is not ready for public use in urban mobility	1	.504**	.343**	.319**	-.209*	-.220*	-.346**
PS-A2 I think Autonomous DRT is a threat to pedestrians	.504**	1	.540**	.443**	-.151	-.072	-.433**
PS-A3 I think Autonomous DRT is a threat to other vehicles	.343**	.540**	1	.452**	-.226*	-.196*	-.323**
PS-A4 I think Autonomous DRT is not secure enough for travelers	.319**	.443**	.452**	1	-.217*	-.102	-.369**
BI1 I Intend to use autonomous DRT occasionally	-.209*	-.151	-.226*	-.217*	1	.493**	.577**
BI2 I intend to use autonomous DRT for my regular trips	-.220*	-.072	-.196*	-.102	.493**	1	.553**
BI3 I would encourage my friends/colleagues to use autonomous DRT	-.346**	-.433**	-.323**	-.369**	.577**	.553**	1

***. Correlation is significant at the 0.05 level (2-tailed).**
****. Correlation is significant at the 0.01 level (2-tailed).**

Table 5 – Correlation matrix behavioral intention and Perceived safety

Looking into the correlation matrix, it becomes apparent that the data from the questions does correlate with one another. In general it can be stated that the questions regarding perceived safety correlate with one another strongly and slightly less but still significantly with those of behavioral intention. Also the questions regarding behavioral intention strongly correlate with one another. Even further supporting the claim that the individual questions can be treated as a factor is the pattern matrix presented in table 6. Here, PS-A1 until PS-A4 all load significantly on component 1 and BI1 until BI3 load on component 2. This proves that the questions relating to their respective constructs indeed answer the same question, but a separate question than the other constructs.

Pattern matrix			
		Component	
		1	**2**
PS-A1	I think Autonomous DRT is not ready for public use in urban mobility	.651	-.091
PS-A2	I think Autonomous DRT is a threat to pedestrians	.879	.092
PS-A3	I think Autonomous DRT is a threat to other vehicles	.758	-.014
PS-A4	I think Autonomous DRT is not secure enough for travelers	.726	.004
BI1	I Intend to use autonomous DRT occasionally	.005	.833
BI2	I intend to use autonomous DRT for my regular trips	.118	.881
BI3	I would encourage my friends/colleagues to use autonomous DRT	-.301	.718

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Table 6 – Component analysis PSA & BI

Factor analysis Performance expectancy, Effort expectancy, Hedonic motivation, perceived safety and behavioral intention

Now the constructs that are part of the UTAUT2 conceptual model and are incorporated in the final conceptual framework of this research are subjected to a principal component analysis.. On top of PS-A and BI, the constructs performance expectancy (PE), effort expectancy (EE) and hedonic motivation (HM) are incorporated. The component matrix in table 7 however only identifies 4 components instead of the 5 mentioned constructs in total. Further investigation revealed that PS-A loads on component 3, EE loads on component 2, HM loads on component 4, but the questions for BI and PE both load on component 1.

This could very possibly be due to the probability of similarity in the answers given in the survey at the questions relating to these concepts. When passengers expect a high performance of the AV, they probably also will have a high behavioral intention to use AVs. So even though PE and BI both load on the same component, both are still treated as different factors. However, PE3 did not seem to load on any component and therefore was omitted from the PE factor. The PE3 question was: "I assume that autonomous DRT will enhance my engagement in activities at the destinations." In the results section, it also became clear that participants reacted differently to this PE related question than to PE1 and PE2. A lot of participants also answered that they neither agreed nor disagreed with this question, indicating that the meaning of the question might have been unclear for the reader.

Pattern matrix

	Components			
	1	**2**	**3**	**4**
PS-A1 I think Autonomous DRT is not ready for public use in urban mobility	-.155	.112	.718	-.133
PS-A2 I think Autonomous DRT is a threat to pedestrians	.195	-.107	.835	.143
PS-A3 I think Autonomous DRT is a threat to other vehicles	-.031	-.159	.775	-.205
PS-A4 I think Autonomous DRT is not secure enough for travelers	.038	.102	.660	.287
BI1 I Intend to use autonomous DRT occasionally	.622	.305	-.028	-.147
BI2 I intend to use autonomous DRT for my regular trips	.695	.077	-.042	.046
BI3 I would encourage my friends/colleagues to use autonomous DRT	.574	.067	-.373	-.066
PE1 I assume that autonomous DRT will help me save travel time.	.556	.045	-.005	-.192
PE2 I assume that autonomous DRT will help me transfer to other transport modes	.804	-.087	.132	.034
PE3 I assume that autonomous DRT will enhance my engagement in activities at the destinations	.256	-.117	-.225	-.312

EE1 I assume it is easy to learn how to use autonomous DRT	-.010	.857	.010	.066
EE2 I assume it is easy to become skillful at ordering autonomous DRT	.066	.811	.006	-.003
EE3 I assume a clear and understandable interaction with the autonomous DRT vehicle	-.002	.809	-.028	-.103
HM1 I think using autonomous DRT is fun	.092	.082	.017	-.860
HM2 I think using autonomous DRT is entertaining	.217	.182	-.079	-.693
HM3 I think using autonomous DRT is enjoyable	-.071	-.049	.072	-.892

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Table 7 – Component analysis PSA,PE,EE,HM & BI

Factor analysis Trust, Media influence, Level of automation, current behavior and perceived safety

The analysis continued by performing a factor analysis on the possible determinants of perceived safety. To do this, another principal component analysis was performed, containing the questions relating to the constructs that theoretically could influence perceived safety of autonomous vehicles. The result of the component analysis is presented in table 8. Even though the level of automation, current behavior and media influence also are expected to potentially influence perceived safety, the questions relating to these cannot be combined into a factor. The current behavior question do not all relate to the same travel mode. The level of automation questions are three separate questions about different levels of automation. And the media influence questions are not expected to have the same kind of outcome since they question a negative subject covered in the media and a positive subject covered in the media. The questions that could be analyzed if they are fit to combine into a factor are related to trust (T). In the component analysis PS-A1 until PS-A4 load on component 1, whereas T1 until T3 load on component 2. Therefore its seems likely that the trust related questions can be combined into a factor.

Pattern matrix		
	Component	
	1	**2**
PS-A1 I think Autonomous DRT is not ready for public use in urban mobility	.572	-.198

PS-A2	I think Autonomous DRT is a threat to pedestrians	.859	.038
PS-A3	I think Autonomous DRT is a threat to other vehicles	.807	.056
PS-A4	I think Autonomous DRT is not secure enough for travelers	.721	-.035
T1	Autonomous vehicles are dependable	.059	.937
T2	Autonomous vehicles are reliable	-.034	.930
T3	Overall, I can trust autonomous vehicles	-.142	.838

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Table 8 – Component analysis Trust & PSA

General overview of results & Representativeness

Summary Stated choice experiment results

The first results to look into are the answers to the SCE. An overview of the choices made in the SCE is presented in table 9. The first thing that is interesting to notice is that autonomous DRT is the most popular option amongst the set of alternatives. In comparison to the results from the pilot it is good to see that the dominance of bicycles as a transport mode has significantly been reduced. Also contrary to the pilot results has seen a spectacular rise in popularity, where car and shared car remain the least chosen alternatives. In general it looks like there is no alternative too dominant as one that is not chosen at all. Therefore it looks like a dataset that is useful for analysis.

Travel mode	**Times available**	**Times chosen**	**Percentage chosen**
Car	945	56	5.93%
Public transport	945	215	22.75%
Shared bicycle	945	254	26.88%
Autonomous DRT	945	308	32.59%
Shared Car	945	112	11.85%

Table 9 – Overview of choices made in SCE

Summary attitudinal questions results

Also the results of the attitudinal questions will be analyzed. Since there is a series of questions that overlap with the study of Curtale et al.(2022), their results will be compared with the answers to the attitudinal questions of this survey. This is useful since the research of Curtale et al. (2022) had a higher number of respondents in both The Netherlands and other countries in Europe. Comparing the results of this survey to their results therefore provides an indication whether the answers given in this survey are representative for the Dutch population. However it is important to mention that in the research of Curtale et al. (2022) their questions concerned electric shared car and autonomous electric shared car. The autonomous electric shared car is a similar vehicle compared to the autonomous DRT, however the DRT is a vehicle shared with other passengers. Therefore results might differ and possible explanations for this will be discussed per construct. An overview of the mean values per question is given in table 10 below.

	Results of this research				**Results Curtale, Liao & Rebalski**			
Constructs	**Mean**	**St dev**	**Skew**	**Construct average**	**Mean**	**St dev**	**Skew**	**Construct average**
PE1	3.21	0.93	-0.43	3.10	3.19	1.07	−0.37	3.24
PE2	3.59	1.12	-0.79		3.34	1.08	−0.47	
PE3	2.51	1.04	0.30		3.18	1.08	−0.30	
EE1	4.55	0.65	-1.59	4.39	3.91	0.89	−0.88	3.89
EE2	4.36	0.81	-1.53		3.89	0.90	−0.85	
EE3	4.26	0.72	-0.75		3.85	0.90	−0.79	
HM1	3.84	0.93	-0.54	3.70	3.35	1.00	−0.48	3.36
HM2	3.79	0.90	-0.55		3.32	0.99	−0.45	
HM3	3.49	1.03	-0.39		3.42	0.98	−0.55	
PSA1	3.70	1.11	-0.55	2.78	3.30	1.06	−0.30	3.15
PSA2	2.49	1.10	0.39		3.02	1.08	−0.07	
PSA3	2.49	1.04	0.38		3.02	1.08	−0.07	
PSA4	2.45	1.03	0.52		3.13	1.03	−0.17	
BI1	3.55	0.99	-0.81	3.16	2.99	1.13	−0.28	2.95

BI2	2.76	1.08	-0.12	3.04	1.16	−0.30
BI3	3.16	0.95	-0.33	2.81	1.18	−0.06

Table 10 – Overview of attitudinal questions comparable with (Curtale, Liao & Rebalski, 2022)

Performance expectancy

The first construct to look into is Performance expectancy. When looking at the results of this study the construct average is 3.10 and that of the comparative study is 3.24. This is fairly comparable with one another. However the constructs belong to fairly different modes of transport in this study versus Curtale et al (2022). The results of this study obviously are related to autonomous DRT, but the other results are related to Electric Shared Car (ESC). Which is neither shared with others during the ride, nor autonomous. Therefore a different study performed in The Netherlands, also using the UTAUT framework to analyze acceptance, is used to compare the results too. The comparison between the studies is added to this analysis to compare whether the sentiment towards the presented constructs is comparable to those in this research. Since both studies have a representative sample, comparing the results could give an indication whether the sample of this research is representative for the Netherlands in terms of sentiment related to the presented UTAUT2 constructs for autonomous vehicles. In a study by Nordhoff et al. (2021) the researchers looked into the acceptance of driverless automated shuttles based on the UTAUT and diffusion of innovation theory (Nordhoff, Malmsten, van Arem, Liu & Happee, 2021). In the research respondents were also asked about the construct Performance expectancy through a set of attitudinal questions, which they needed to answer on a six point Likert scale after a trip in a driverless shuttle. Whilst this is also not completely comparable to the results of this study, since the questions differ, the circumstances of the survey taken differ and this research uses a 5 point Likert scale, it might give an indication whether the results are somewhat similar. Looking into the mean of the construct Performance expectancy in the research of Nordhoff et al. (2021) a score of 3.47 is reported. This is slightly higher than the 3.10 reported in this study, however this might be due to the difference in Likert scales.

Likert scale	**Count of PE1**	**Count of PE2**	**Count of PE3**
1	4	7	18
2	20	12	37
3	35	18	31
4	42	48	16
5	4	20	3
Total	**105**	**105**	**105**

Table 11 – Frequency of responses per level to attitudinal questions related to Performance expectancy

In general it can be stated that the respondents of this research expect that autonomous DRT will enhance their travel performance. Although it also must be mentioned that 3.10 is not a value much above the 3.0 and therefore the expected performance increase is not perceived as spectacular by the respondents of this survey. Looking into the answers given to the questions in table 11, it is also apparent that a lot of the respondents answered 3, which is "neither agree or disagree". This could also indicate that people simply do not know yet whether autonomous DRT would increase their travel performance.

Effort expectancy

When comparing the results of effort expectancy with those of Curtale et al. (2022) the same issue as with performance expectancy arises. All that can be concluded from comparing these results, with a score of 4.39 for this research and 3.89 in Curtale et al. (2022), is that people perceive the effort associated with autonomous drt as lower than the effort of using a shared electric vehicle. Therefore again it is interesting to look at the results of Nordhoff et al. (2021) as well. Even though, as mentioned before, the study of Nordhoff et al. (2021) isn't completely comparable with this study. Interestingly enough, the value of the mean of the construct effort expectancy from the survey of Nordhoff et al. (2021), has a value of 4.42. This again is slightly higher than the results of this study. In terms of representativeness of the sample of this study for the population of The Netherlands that is a positive sign.

Likert scale	Count of EE1	Count of EE2	Count of EE3
1	0	1	0
2	2	3	2
3	3	7	11
4	35	40	50
5	65	54	42
Total	**105**	**105**	**105**

Table 12 – Frequency of responses per level to attitudinal questions related to Effort expectancy

Where the respondents were somewhat more hesitant towards the expected performance increase from using Autonomous DRT, there is little to no ambiguity concerning the expected effort, or in fact lack thereof, affiliated with using the transport mode. As is seen as well in table 12, the majority of the respondents feel that the effort associated with using or learning to use Autonomous DRT is limited.

Hedonic motivation

Now the construct of hedonic motivation is evaluated. Contrary to the previous two constructs, the questions in the research of Curtale et al. (2022) did concern autonomous shared electric cars. Therefore the value of this research is better comparable with their value opposed to the values of the previous constructs. This research reports a 3.70 mean for hedonic motivation, whereas Curtale et al. (2022) show a 3.36 mean value. The appeal of an autonomous DRT therefore seems slightly higher than that of an autonomous shared electric car. However, what is important is that the values seem to exert the same conviction of the participants concerning hedonic appeal of autonomous transport modes. Which in turn is favorable for the expected representativeness of this study for the Dutch population.

Likert scale	**Count of HM1**	**Count of HM2**	**Count of HM3**
1	1	1	4
2	8	8	13
3	25	25	33
4	44	49	38
5	27	22	17
Total	**105**	**105**	**105**

Table 13 – Frequency of responses per level to attitudinal questions related to Hedonic motivation

As the Mean value indicates, when looking at the count of the answers in table 13 an overall trend of hedonic appeal of autonomous DRT can be recognized. However, same as with Performance expectancy, it seems that participants can still be puzzled about their feelings towards the fun of using an Autonomous DRT. Amongst the different questions, participants frequently answered with 3 (neither agree or disagree). Therefore the statements made concerning hedonic motivation cannot be made with the same certainty as those of effort expectancy.

Perceived safety

This is an important construct to look into, since a large part of this research is to look into the effect of perceived safety on acceptance of autonomous DRT. When analyzing the values of the perceived safety construct, it is important to keep in mind that the meaning of the value is somewhat counter intuitive. To clarify, the lower the value of perceived safety, the higher the perceived safety of autonomous DRT of the participant is. This is due to the formulation of the questions in the research. An example would be PSA1: "I think Autonomous DRT is not ready for public use in urban mobility.". Since disagreeing with this question would indicate that the participant perceives autonomous DRT as safer, the lower the mean value of the perceived safety construct, the higher the actual perceived safety of the mode. Comparing the construct values of this survey and Curtale et al. (2022), with respective values of 2.78 and 3.15 one could argue that autonomous DRT is perceived as somewhat safer than Autonomous shared car. However in this case the bias of the sample of this research might have quite an influence. As explained before, this research made use of snowball sampling. This resulted in a sample of participants that are part of the transport and mobility department of TNO and also a large group of students of the TPM faculty of TU Delft. Because the participants in these groups are highly likely educated on the subject of autonomous mobility, chances are that they might perceive the safety of autonomous vehicles differently than the average Dutch person. Therefore, stating that autonomous DRT is perceived as safer than Autonomous shared car would probably not be a right representation of the Dutch population's opinion towards both modes.

Likert scale	**Count of PSA1**	**Count of PSA2**	**Count of PSA3**	**Count of PSA4**
1	2	20	17	17
2	19	41	44	46
3	15	20	22	23
4	41	21	20	16
5	28	3	2	3
Total	**105**	**105**	**105**	**105**

Table 14 – Frequency of responses per level to attitudinal questions related to perceived safety

When looking into the answers to the questions about perceived safety there are many similarities in the answers for questions PSA2, PSA3 and PSA4. The dissonant in the set of questions is PSA1. In PSA2, PSA3 and PSA4 it is seen that most of the people lean towards disagreeing with the statement. However in PSA1 most of the participants seem to agree with the statement. To increase understanding of this difference, the questions as presented in the survey are presented below again:

PSA1: I think Autonomous DRT is not ready for public use in urban mobility.

PSA2: I think Autonomous DRT is a threat to pedestrians

PSA3: I think Autonomous DRT is a threat to other vehicles

PSA4: I think Autonomous DRT is not secure enough for travelers.

It seems that participants in general feel that Autonomous DRT is not a threat to pedestrians, other vehicles and is secure enough for travelers. However the participants generally also seem to feel that Autonomous DRT is not ready for public use in urban mobility yet. It is interesting to notice that, since it immediately raises the question why. It seems from the answers of the other questions that the autonomous DRT is not perceived as unsafe. Therefore it might be that participants see other limitations to the implementation of autonomous vehicles in urban mobility that are not captured by this question. The reason PSA1 therefore might differ in general attitude towards the question, is that participants did not review it as a safety question at all. At this point arguing what other factors influence the perceived readiness of autonomous DRT for the public road, would be nothing more but speculation. Hopefully analyzing the results in the statistical models could provide some more insights in this discrepancy of answers between PSA1 and PSA2,PSA3 and PSA4. Otherwise it could be a subject for future studies.

Behavioral intention

The last of the constructs to be compared with Curtale et al. (2022) is behavioral intention to use Autonomous DRT. For this construct the same limitation of comparison arises as mentioned before, since the vehicle types are not completely the same. However when looking into the values of the different studies, a value of 3.16 is reported for this study and 2.95 in Curtale et al. (2022). Since Nordhoff et al. (2021) also gathered information about Behavioral intention, their mean value of 4.24 also can be used in the comparison. Again it can be observed that the attitude towards behavioral intention to use the travel modes is positive. In general the participants seem to lean more towards accepting the technology then resenting it. The magnitude of reported intention to use does differ amongst the research. Whilst the difference between this research and Curtale et al. (2022) is not large, there seems to be a slight preference towards using autonomous DRT. This is also seen in the high value in Nordhoff et al. (2021), yet it must be stated that this research made use of a 6 point Likert scale.

Likert scale	**Count of BI1**	**Count of BI2**	**Count of BI3**
1	5	16	6
2	10	25	16
3	25	35	44
4	52	26	33
5	13	3	6
Total	**105**	**105**	**105**

Table 15 – Frequency of responses per level to attitudinal questions related to Behavioral intention

When analyzing the responses of the participants of this survey, it becomes apparent that there still is quite some uncertainty amongst the sample concerning behavioral intention. Even though amongst all the different questions the participants might lean towards accepting Autonomous DRT, there still is a large group that is ambiguous about it or even opposed.

Attitudinal questions added to research determinants of perceived safety

Amongst the sets of questions presented to the participants of this survey, also were a couple that were specifically designed for this research. They contained questions about the current behavior, trust in AV, media influence and level of automation. An overview of the mean values is presented in table 16.

Variable	Mean	St dev	Skew
CB1	3.12	1.52	-0.16
CB2	3.74	1.28	-0.74
CB3	4.40	1.00	-1.83
CB4	1.38	0.89	2.40
T1	3.09	0.84	-0.17
T2	3.06	0.96	-0.12
T3	3.13	1.12	-0.23
MI1	3.06	1.08	-0.07
MI2	3.49	0.96	-0.45
MI3	3.17	1.10	-0.61
LA1	3.80	0.84	-0.71
LA2	4.02	0.93	-0.99
LA3	3.09	1.06	-0.12

Table 16 – Overview of attitudinal questions composed for this research

Current behavior

The participants were asked about which modes of transport they would usually use for inner city trips. CB1 is a car, CB2 is public transportation, CB3 is a bicycle and CB4 is a shared car. In table 17 the overview of answers from the survey is presented. What stands out is that about 50% of the participants indicate that they regularly use a car for inner city travel, whereas in the stated choice experiment the car represented a mere 5.93% of the total choices made. The values for public transportation and bicycle are more easily matched with the results of the SCE, however in the attitudinal question asked about the use of regular bicycles and not a shared bicycle. About 7% of the participants use a shared car regularly, which would be in line with the 11.85% in the stated choice experiment. Even though the values of car use in the SCE versus the attitudinal questions seems to differ a lot, it also doesn't say a lot. The SCE is designed in a way to provoke trading behavior amongst the participants and not reflect their actual current behavior. Therefore the scenarios and attribute levels as presented for cars indeed achieved the possibility of people switching their behavior to a different travel mode. Another possible explanation of this difference could be that autonomous DRT mainly would be a consideration for participants that usually use cars. This will be analyzed later on in the report.

Likert scale	Count of CB1	Count of CB2	Count of CB3	Count of CB4
1	23	6	3	85
2	20	20	4	8
3	9	6	9	5
4	27	36	21	6
5	26	37	68	1
Total	**105**	**105**	**105**	**105**

Table 17 – Frequency of responses per level to attitudinal questions related to Current behavior

Trust

When it comes to trust in autonomous vehicles in general the participants seemed a bit hesitant. As is seen in table 18 there are few entries that completely agree or disagree with the statements and a large group per question seems not to have made up their mind about it completely and chose for option 3. This is possibly due to the very limited availability of autonomous vehicles, however that would contradict the previous made statements about perceived safety and the bias of the sample. In general the only thing to really say about the data from this question is that there are no strong feelings involved with trust in autonomous vehicles, positive or negative.

Likert scale	Count of T1	Count of T2	Count of T3
1	3	5	9

2	21	25	22
3	48	39	30
4	30	31	34
5	3	5	10
Total	**105**	**105**	**105**

Table 18 – Frequency of responses per level to attitudinal questions related to Trust

Media Influence

In table 19, the results of the questions about media influence are presented. MI1 and MI2 ask about specific media content and MI3 aims to validate whether people are affected by media content. MI1 states that when reading about AV in the media it usually pertains to accidents related to the technology. An interesting split is seen amongst the participants, where about as much people agree as disagree with this statement. This is different in MI2, where the question was about media content being preoccupied with the benefits of the technology. A larger partition of the respondents agreed to that statement. Also people in general seem to be influenced by media content. However for this specific question again the bias of the sample might be an issue. People working at TNO and studying at TU Delft might be prone to receiving relevant information about Autonomous Vehicles, whereas any other Dutch citizen might go years without hearing or reading about it.

Likert scale	Count of MI1	Count of MI2	Count of MI3
1	7	2	12
2	29	17	14
3	28	26	29
4	33	48	44
5	8	12	6
Total	**105**	**105**	**105**

Table 19 – Frequency of responses per level to attitudinal questions related to Media influence

Level of automation

The questions regarding Level of automation asked the participants to indicate to what extent they would feel safe as a passenger in a vehicle with various levels of automation. LA1 asked this for a level 0 autonomous vehicle, so a completely human driven car. LA2 for a level 4 autonomous vehicle, so a vehicle that is completely self-driving, but has a human driver present to intervene in case of emergency and LA3 for a level 5 autonomous vehicle where no human driver is present at all and the vehicle is fully self-driving. Looking into the answers given in table 20, it is clear that the level 4 car is considered the vehicle in which passengers would feel safest and the level 5 car passengers would feel the least safe. Remarkable, considering that both these vehicles are completely self-driving, with the only difference being that in the level 4 vehicle a human driver is present in case of emergency. Especially since the level 4 autonomous vehicle seems to be valued as safer than the level 0 human driven car. Participants therefore seem to indicate that they consider a self-driving car to be safer than a human driven car, but only when a human is present to intervene. A possible explanation could be that passengers feel safer when a kind of emergency safety net is present. In level 0 and level 5 the vehicle relies on the solely on the abilities of the human driver and the autonomous vehicle AI, but the level 4 vehicle has the safety net of a human driver when the AI of the vehicle would malfunction. Sadly there was no question incorporated questioning the a vehicle with a human driver and an autonomous system that could intervene in case of emergency. Because that could have enforced this proposed safety net theory.

Likert scale	Count of LA1	Count of LA2	Count of LA3
1	1	2	7
2	7	5	25
3	22	17	33
4	57	46	32
5	18	35	8
Total	**105**	**105**	**105**

Table 20 – Frequency of responses per level to attitudinal questions related to Level of Automation

Summary socio demographics

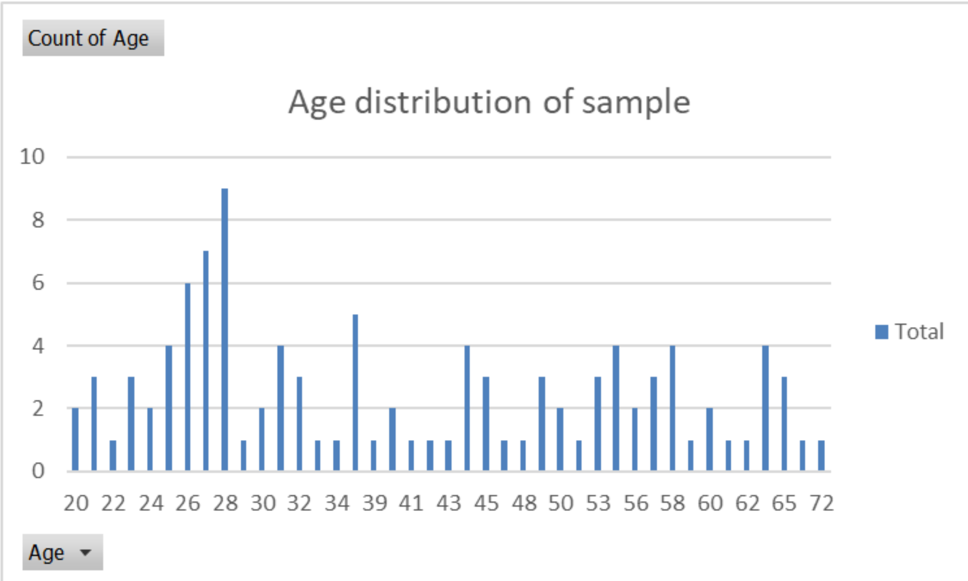
In this section, the socio-demographics of the participants will be analyzed and compared to sociodemographic values of the Netherlands, in order to evaluate to what extent the sample is representative for the Dutch population in terms of socio-demographic statistics. Also differences compared to the Dutch population are analyzed and possible theories for these differences are presented.

Age

The first socio-demographic characteristic to be discussed is age. For this comparison it is important to take into account that the age group 0-18 was excluded from participation in the survey. However even without this group, the majority of participants of the survey are relatively young compared to the actual Dutch population. This initially is not that apparent when looking into the mean age of both data sets in table 21, with 40,38 as the mean age for the data of this survey and 42,3 the national mean age. However when comparing the percentages per age group and when looking into graph 1 it becomes apparent that the majority of the sample belongs to the 20-40 age group, with a peak of participants in their late 20's. This is probably due to the snowball sampling method used for this survey. Due to this recruitment method many participants were drawn from the network of the researchers involved in this master thesis. Considering the principal investigator of this research also is in his late twenties, this is not a surprising statistic and more similarities between the researchers and sample probably will appear.

	Values from this survey	**Percentages**	**CBS Netherlands**
Mean	40.38	-	42,3
0-19	0	0	21%
20-40	57	54%	25%
41-64	43	41%	34%
65+	5	5%	20%

Table 21 – Overview of age groups ("Leeftijdsverdeling", 2022)



Graph 1 – Age distribution

Gender

There is a slight overrepresentation of male participants in the sample compared to the Dutch average. However in general the division in gender can be considered quite balanced.

	Sample	Netherlands
Male	56%	49.7%
Female	44%	50.3%

Table 22 – Gender ("Men and Women", 2022)

Level of education

Concerning level of education the sample of the survey is quite extremely high educated compared to the Dutch division. Participants in possession of or enrolled in a HBO bachelor study or higher were considered highly educated and the other participants fell in to the lower level of education category. In table 23 it is observed that 95% of the participants was in possession of a HBO or WO bachelor degree or was currently enrolled in a study of the same level. This again is probably due to the participant recruitment method. The networks that were utilized for recruitment of participants consisted of students at the TU Delft and professors and researchers at the TU Delft and TNO. When the direct network of these people is tapped into a high education rate can be expected.

	Sample	Netherlands

Higher	95%	30.0%
Lower	5%	70.0%

Table 23 – Level of education ("Onderwijs - Cijfers - Maatschappij", 2022)

Car driver's license

As can be seen in table 24, there are some more participants that own a car driver's license compared to the national numbers.

	Sample	**Netherlands**
No license	9%	20,0%
license	91%	80,0%

Table 24 – Car driver's license ownership ("80 Procent volwassenen heeft rijbewijs", 2022)

Car ownership

In terms of car ownership, a smaller percentage of the sample owns a car compared to the Dutch population. This could be related to the relatively young age of the sample.

	Sample	**Netherlands**
No Car	33%	48%
Car	67%	52%

Table 25 – Car ownership (Busser, 2022)

Income

For the division between low income participants and high income participants, the average Dutch income was used. Participants with an income above the Dutch average income were considered high income participants and participants below the average as low. Within the sample there is a relatively high percentage of individuals with a high income. This probably also is related to the high level of education of the sample.

	Sample	**Netherlands**
Prefer not to tell	16%	
Low	26%	77,5%

High	58%	22,5%

Table 26 – Income per person ("Verdeling gestandaardiseerd inkomen", 2022)

6. Analysis and results

In this chapter the outcomes of the statistical analysis will be discussed. The gathered data from the survey was subjected to several different models in order to reveal significant, and insignificant, relations amongst the various constructs. The analysis helps to answer the research question as presented in chapter two and utilizes the methods described in chapter 4 of this report.

MNL generic estimates attributes and time combined

The first method of analysis that was executed on the data was an MNL model making use of the Apollo software in the RStudio environment. The code of the model is presented in Appendix C. The code used for this model can be considered the base code for all the following MNL models. For the other models, the same structure was used, but the incorporation of parameters was interchanged in order to find an optimal model to explain the research questions. The outcome of the first model as presented in table 27, assumed that the attributes presented in the SCE can be generalized for the different travel modes. In other words, the attributes all have the same effect on different travel modes, regardless of the difference between the modes. This is mainly to perform a first check on the robustness of the gathered data.

Model log likelihood and Rho squared	**Value**		
LL (final)	-1118.88		
Adj.Rho-square (0)	0.261		
Parameter	**Estimate**	**Standard error**	**T-ratio**
BETA_TT	-0.1294	0.008094	-15.987
BETA_AE	-0.1365	0.012633	-10.805
BETA_W	-0.1233	0.013751	-8.966
BETA_TC	-1.0404	0.056902	-18.284
BETA_PC	-0.4066	0.033211	-12.242

Table 27 – MNL results estimating generic parameters for the modes

In the results, five parameters are estimated: BETA_TT, BETA_AE, BETA_W, BETA_TC, BETA_PC. These are the respective estimates of the attributes travel time (BETA_TT), access and egress time (BETA_AE), waiting time (BETA_W), travel cost (BETA_TC) and parking cost (BETA_PC). The signs of the estimates are all as expected, since an increase of either of the attributes is expected to decrease the utility of the travel mode. This is a good indicator predicting validity of the gathered results. Another good indicator is the T-ratio of the estimates. Generally speaking a T-ratio exceeding 1.95 or -1.95 indicates that the estimate is significant. Looking into the T-ratio of the estimates of this model all exceed it by quite a large amount, which is another good sign whilst judging the robustness of the data. The rho squared value of the model is also presented in the table. The rho squared value is regarded as an indicator for the goodness of fit of the model with the data. In general a rho squared value ranging between 0.2 and 0.4 represents a good fit of the model with the data (McFadden, 1977). The rho squared value of this model is 0.261 and therefore once more a good sign for the exploratory value of the data.

Something that does become apparent in the estimates is that the values relating to time, do not significantly differ from one another. This indicates that the travelers do not value waiting time, access and aggress time or on board travel time any different, but rather just care about the total travel time of a trip. Therefore the time related variables are combined to a total travel time attribute (BETA_TTTotal). This resulted in the estimates presented in table 28. In this subsequent model, the Alternative specific constants of the travel modes were also incorporated. The alternative specific constants capture the effects of factors that are not incorporated in the model. As can be seen from the results, the T values of the estimates decreased and the rho squared value somewhat increased. Meaning that the significance of the estimated parameters decreased, and with increasing the amount of parameters the model gained exploratory value. Estimating travel time as a total and in 3 different forms has been done in the subsequent MNL model as well, generating the same kind of outcome as in this model. Therefore, travel time is regarded as a combined variable.

Model log likelihood and Rho squared	**Value**		
LL (final)	-1095.28		
Adj.Rho-square (0)	0.2753		
Parameter	**Estimate**	**Standard error**	**T-ratio**
Asc_car	0.06544		0.1138
Asc_pt	1.36783		4.8910
Asc_bic	1.45745		5.3317
Asc_adrt	1.06611		6.5009
Asc_sc	0.00000	NA	NA
BETA_TTTotal	-0.19640	0.01820	-10.7897
BETA_TC	-0.78230	0.07191	-10.8792

BETA_PC	-0.34726	0.10616	-3.2712

Table 28 – MNL results estimating generic parameters and asc for the modes combining all times

Another method to further check whether the results make sense and are close to the Dutch attitude towards travel, is to look into the value of travel time (VOTT). VOTT can be described as the willingness to pay (WTP) for a unit-travel time. The Dutch national average of VOTT for a standard car is €9.30-€9.90/hour (Yap, Correia & van Arem, 2016). When looking into the results presented in table 12 an estimation of VOTT can be made by dividing the estimate of BETA_TTTotal by BETA_TC and multiply this by 60 since the questions presented to the participants were in minutes. Doing this generates a VOTT of €15,06/ hour. Compared to the national average for car this might be a bit on the high side.

MNL extended with alternative specific constants, mode specific estimates, socio demographics and perceived safety

The findings in the previous paragraphs indicate that the gathered data is robust and forms a solid basis for further analysis and interpretation. However the model as presented didn't contain the information needed to answer the research questions of this project. Therefore, an extended MNL model is designed containing additional estimates like alternative specific constants, mode specific attribute estimates, socio-demographics and perceived safety. The socio-demographic parameters that are incorporated were chosen based on an iterative process, where first all sociodemographic parameters were incorporated and one by one the insignificant parameters were removed until only the significant remained. This resulted in the incorporation of both age and gender, but the exclusion of level of education, income, car ownership and possession of a driver's license. In Table 29, the results of the Extended MNL model are presented.

Model log likelihood and Rho squared	**Value**		
LL (final)	-1058.65		
Adj.Rho-square (0)	0.2882		
Parameter	**Estimate**	**Standard error**	**T-ratio**
Asc_car	0.32745	1.685274	0.1943
Asc_pt	- 3.63663	1.619660	- 2.2453
Asc_bic	- 2.38850	2.535150	- 0.9422
Asc_adrt	3.78642	1.372271	2.7592

Asc_sc	0.00000	NA	NA
BETA_TTTotalCar	- 0.19859	0.052856	-3.7571
BETA_TCcar	- 0.74672	0.223405	-3.3424
BETA_PCcar	- 0.44183	0.116117	-3.8051
BETA_TTTotalPt	- 0.07486	0.035781	-2.0923
BETA_TCpt	- 0.52494	0.221306	-2.3720
BETA_TTTotalBic	- 0.12262	0.065834	-1.8626
BETA_TCbic	- 0.45072	0.190795	-2.3623
BETA_TTTotalAdrt	- 0.27774	0.033509	-8.2886
BETA_TCadrt	- 0.73834	0.216158	-3.4157
BETA_TTTotalSc	- 0.18144	0.045668	-3.9731
BETA_TCsc	- 0.75875	0.159497	-4.7571
BETA_Gender_adrt	- 0.12472	0.138844	-0.8983
BETA_Age_adrt	0.01466	0.009786	1.4979
BETA_Gender_car	- 0.33252	0.181465	-1.8324
BETA_Age_car	0.01243	0.012932	0.9609
BETA_Gender_pt	- 0.28620	0.128943	-2.2196
BETA_Age_pt	0.02784	0.009152	3.0422
BETA_Gender_bic	- 0.20620	0.124064	-1.6620
BETA_Age_bic	0.02997	0.008812	3.4013
BETA_PSA_adrt	- 0.45155	0.122936	-3.6731

Table 29 – MNL results including asc, relevant sociodemographics and perceived safety

The rho squared value of this model is 0.2882 and therefore shows a slight increase compared to the previous model. The rho squared value remains within the 0.2-0.4 window and therefore indicates that there is a good fit of the model with the data. The VOTT could now be calculated per mode and resulted in the following numbers:

Car: € 15,96/h

Public transport : €8,56 /h

Shared bicycle: €16,32 /h

ADRT: €22,57 /h

Shared car: €14,35 /h

Considering that the national average of VOTT for car is around 66% higher in this model is somewhat strange. A possible explanation for the increased VOTT is the relatively high percentage of high income participants of this survey. 58% of the participants belonged to the high income group, compared to 22% for the Dutch population. However this would somewhat contradict the result of the design of the model. Since Income was incorporated, but proved not to be a significant parameter for any of the travel modes. Another possible explanation for the drastic increase could be the recent inflation of travel costs and costs in general. Since this survey has been conducted in a time period of increasing fuel prices, it might be that participants have a higher VOTT compared to 2016, which is the year the national average VOTT for cars was derived from.

Even though the VOTT calculated probably is somewhat inflated, it can still serve to examine the relative difference amongst the different travel modes. Especially comparing ADRT with the other modes, since it provides insights in the determinants of ADRT acceptance. Interestingly the VOTT for ADRT is the highest of all the other alternatives. Meaning that passengers are willing to relatively pay more compared to other modes to reduce their travel time in an ADRT.

Looking into the alternative specific constants, there are two significant values reported. The values of ADRT (Asc_adrt) and public transportation (Asc_pt). In this case, it also reveals that travelers seem to have a preference for driving ADRT compared to public transportation.

The sociodemographic variables that generated significant estimates were age and gender. Gender was effect coded in the model with a value of -1 for female and 1 for male. Amongst the different modes, the sign of the estimates all are negative, which would indicate that female travelers would have a preference for all modes. This obviously is a very strange result and cannot be stated since the only significant estimate related to gender is that of public transport (BETA_Gender_pt). The only thing related to gender that can be stated based on the results of this model therefore is that public transportation is a travel mode more appealing to female passengers. Age has a couple more significant estimates, however the one that is most important to this research (BETA_age_adrt) is not significant. When it comes to the socio demographic parameters included in this research influencing travel behavior, sadly no significant results can be reported. This might be due to the relatively low number of participants to the survey (105).

Another parameter that was included in the MNL model is perceived safety (BETA_PSA_adrt). The perceived safety was questioned in the attitudinal questions part of the survey. It was incorporated in the model and revealed a negative relation to the utility of ADRT. This actually means that the higher the traveler perceives safety of AV's, the higher the likelihood of accepting the travel mode. This might sounds counterintuitive because of the negative sign of the estimate, but this is due to the formulation of the questions in the survey. The participants had to answer a Likert scale question that has an inverse relation with perceived safety. Meaning the higher the reported value in the survey the lower perceived safety. To clarify, this is an example of one of the questions: “I think Autonomous DRT is not ready for public use in urban mobility.”. This is a first indication that perceived safety is indeed a significant construct impacting the acceptance of ADRT.

Multiple regression determinants of perceived safety

After it was established that the trust related questions could be combined, a new factor was created named Mean_T and incorporated in the model. The questions relating to the constructs current behavior (CB), media influence (MI), Level of automation (LA) and the factor of trust were modelled in a multiple regression analysis with the factor of perceived safety (Mean_PSA) as a dependent variable. CB1 asked participants whether a mode of transportation they frequently used was car, CB2 public transportation, CB3 bicycle and CB4 shared car. MI1 & MI2 were also incorporated with MI1 asking participants to indicate their agreement that news that involved AV’s usually is about accidents and MI2 about the benefits of the technology. MI3 was excluded, since this was a question asking participants whether they felt that they were influenced by media reports. LA1 asked whether the participants felt safe in a level 0 AV (human driver), LA2 a level 4 AV (Autonomous with human backup) and LA3 a level 5 AV (fully autonomous). The results of the multiple regression analysis are displayed in table 30.

The analysis did not provide a lot of significant relations. Only Mean_T and LA3 showed t-values and significance levels that indicate a significant relation between the variable and perceived safety. Both of the estimates had a negative sign. As explained before, the lower the reported perceived safety value in the survey, the higher the actual perceived safety. Therefore, the negative sign indicates that when the value of the variables rise, perceived safety of AV also increases. Starting with LA3, from the results it can be concluded that the higher people indicate that they feel safe in a level 5 autonomous vehicle, the higher perceived safety of av’s in general. Also the lack of a significant relation between LA1 and LA2 with perceived safety, could mean that only when passengers would feel safe in level 5 autonomous vehicle that has a positive effect on the general perceived safety of AV. This therefore is a good indication that level of automation in general influences perceived safety of autonomous vehicles. The same kind of relation is identified between trust and perceived safety. The higher the trust in the autonomous vehicle technology, the higher the perceived safety of autonomous vehicles.

The questions related to media influence did not yield a significant relation between media influence and perceived safety. This could indicate that media coverage of news surrounding autonomous vehicles does not influence perceived safety of autonomous vehicles, regardless of it being positive or negative. However it could also mean that the survey did not contain enough respondents to generate a significant result. Another explanation has to do with the bias in the sample. Since a lot of the participants were in the network of TU Delft students studying CoSem as well and employees of the Transport and logistics department of TNO, it could be that this group of participants is less influenced by reports about AV on the news because it is part of their study and research. So instead of basing their opinion on media coverage, it will rather be shaped by relevant scientific literature or their own research. Also not any of the current behavior questions displayed a significant relation with perceived safety.

Coefficients					
	Unstandardized Coefficients		Standardized coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	2.999	.846		3.543	.001
CB1	.035	.053	.066	.657	.513
CB2	.052	.062	.081	.834	.406
CB3	.090	.076	.111	1.182	.240
CB1	.115	.084	.126	1.365	.176
MI1	.012	.066	.016	.177	.860
MI2	.019	.076	.023	.252	.801
LA1	.102	.094	.105	1.077	.284
LA2	.009	.087	.010	.104	.918
LA3	-.165	.084	-.215	-1.956	.053
Mean_T	-.353	.099	-.392	-3.582	.001

Dependent Variable: Mean_PSA

Table 30 – Coefficients multiple regression CB,MI,LA, T & PSA

Linear regression perceived safety on behavioral intention ADRT

After the factor analysis was performed, the next step was to look into the relation between the factors. To generate the factors of the constructs, the mean of the construct questions was generated in SPSS. This resulted in the variables Mean_PSA and Mean_BI. This was followed by linear regression modelling with Mean_BI as a dependent variable of Mean_PSA. The coefficients of that analysis are portrayed in table 31. Looking into the t-value and significance level of the Mean_PSA variable it can be stated that perceived safety of AV's significantly influences behavioral intention to use AV. The following question is how does it influence behavioral intention. Since the sign of the estimate (B) is negative it means that the higher PSA, the lower BI. However for this relation the same applies as explained in the MNL model regarding perceived safety. The questions have an inverse relation to the actual construct, meaning the lower the reported value for perceived safety, the higher the actual perceived safety of AV's actually is. The outcome of this analysis therefore supports the claim, based on the MNL model results, that increased perceived safety positively influences the acceptance of ADRT services.

Coefficients					
	Unstandardized Coefficients		**Standardized coefficients**		
	B	**Std. Error**	**Beta**	**t**	**Sig.**
(Constant)	4.226	.274		15.431	.000
Mean_PSA	-.384	.095	-.371	-4.057	.000

a. Dependent Variable: Mean_BI

Table 31 – Coefficients linear regression PSA on BI

Multiple regression UTAUT2 and perceived safety on behavioral intention

The UTAUT2 related questions were combined into their respective factors in the same way as perceived safety and behavioral intention. In this way the factors for hedonic motivation (Mean_HM), effort expectancy (Mean_EE) and performance expectancy (Mean_PE) were created. Through multiple regression the relation between the UTAUT2 constructs and behavioral intention to adopt AV was analyzed. This resulted in the coefficients portrayed in table 32. The t-values and the significance levels revealed that the incorporated variables all had a significant effect on Mean_BI. The estimates of the variables also had the expected sign. Positive for hedonic motivation, effort expectancy and performance expectancy and negative for perceived safety. As explained before the negative sign of perceived safety does not mean that the higher the perceived safety the lower the behavioral intention to adopt. Therefore all the incorporated factors have the same type of relation with BI, meaning if the respective values of the constructs increase the behavioral intention to adopt ADRT also increases.

Since all the variables display a significant relation and all rated on the same scale, the magnitude of the estimates could also be compared. Effort expectancy and performance expectancy both have the highest impact on acceptance of ADRT. This means that when potential passengers of ADRT expect that the effort needed to accept the technology is low, the quicker they will accept ADRT as a possible means of transportation. The same applies to Performance expectancy. Passengers that expect ADRT to improve their travel performance, will be more likely to accept the technology. A slightly less impactful, but also significant, influence on the acceptance of ADRT is hedonic motivation. The relation as presented in table

33 shows that an increase in enjoyment or fun of a trip with an ADRT also increases the chance of acceptance. Whilst passengers value performance and effort expectancy more in their decision, hedonic motivation also plays a part. The least impactful variable amongst the four modeled ones is perceived safety. Same as in the previous model solely containing the concepts behavioral intention and perceived safety, Mean_Psa shows the same significant relation with behavioral intention to use ADRT. So this model also confirms that the higher the perceived safety of autonomous vehicles, the higher the chance that ADRT is adopted by the travelers. Compared to the other constructs, however, it reports the lowest estimate, meaning that travelers are impacted more by a change in valuation of the other constructs than that of perceived safety.

Coefficients					
	Unstandardized Coefficients		**Standardized coefficients**		
	B	**Std. Error**	**Beta**	**t**	**Sig.**
(Constant)	.358	.627		.572	.569
Mean_PSA	-.194	.083	-.188	-2.353	.021
Mean_HM	.265	.088	.262	3.023	.003
Mean_EE	.315	.107	.230	2.939	.004
Mean_PE	.315	.096	.285	3.266	.001

Dependent Variable: Mean_BI

Table 32 – Coefficients multiple regression PSA,PE,EE,HM & BI

7. Conclusions, limitations & recommendations

Conclusion

To sum up the findings of this research, all the sub questions are answered based on the findings presented in the previous section, followed by a more general answer to the main research question. All claims that are made in the conclusions only apply to travelers in an urban environment, making short inner city trips.

1. ***What is the impact of travel time on autonomous DRT acceptance?***
2. ***What is the impact of travel cost on autonomous DRT acceptance?***
3. ***What is the impact of parking cost on autonomous DRT acceptance?***

A general remark relating to travel time is that travelers do not value waiting time, access and aggress time or on board travel time any different, but rather just care about the total travel time of a trip. This is not specifically for ADRT, but that same effect was found for all the different travel modes in the analysis.

Further analysis of the impact of travel cost and travel time revealed that ADRT had the highest VOTT compared to all of the other alternatives. Meaning that passengers are willing to pay more compared to the other modes, in order to reduce their travel time in an ADRT. This was mainly due to the relative magnitude of the travel time estimate of ADRT compared to the other modes. With -0.27774 it showed the highest weight of increased travel time, car following in second place with -0.19859 and an even bigger difference compared to public transportation that reported a weight of -0.07486.

The differences amongst the modes were less staggering for the estimates of travel cost. Where ADRT scored somewhere along the middle with - 0.73834 compared to the highest number of shared car - 0.75875 and the least impactful of bicycle - 0.45072. Generally speaking, it can therefore be stated that travel time is a more impactful attribute influencing the acceptance of ADRT services compared to the cost of the trip. However, this could also have been due to the exceptionally high number of high income individuals that partook in the survey. If someone is in the possession of copious amounts of money, then it indeed makes sense that time is valued over cost. However, if more participants with a lower income would have participated, the outcome might have been different.

But based on the performed analysis to improve the chances of acceptance of the technology, efforts are best to go towards minimizing travel time. This could be achieved through optimization of the routing software in the ADRT or ensuring sufficient availability at all times. Also, infrastructural measurements can be taken that either decrease the travel time of the ADRT (as for instance dedicated lanes for ADRT transportation) or increase travel time for other means of transport (like restricting access to certain roads or areas by car).

Lastly, the relative importance of parking cost on the adoption of ADRT is reviewed. Since the ADRT itself does not have parking costs affiliated with a trip made, the only way to review the impact of parking cost is indirect through the effect parking cost has on the travel mode car. When looking into this, it indeed becomes apparent that parking cost significantly influence the decision to choose for the car option. However it has a relatively smaller impact on utility compared to travel costs. Therefore, acceptance of ADRT services would indeed be impacted by rising or decreased parking costs. However changes in regular travel costs (as for instance rising gasoline prices), would have a bigger effect on the decreased utility of car and therefore increased utility for ADRT.

4. ***What are the determinants of AV safety perception and to what extent do they influence AV safety perception?***

Analyzing the results containing the data of the determinants of perceived safety, not a lot of significant relations between the variables and perceived safety were identified. Trust and level of automation did portray a significant relation with perceived safety. The higher people indicated that they would feel safe in a level 5 autonomous vehicle, the higher perceived safety of AV's in general. Also the lack of a significant relation between LA1 and LA2 with perceived safety, could mean that only when passengers would feel safe in a level 5 autonomous vehicle, it will have a positive effect on the general perceived safety of AV. This therefore is a good indication that level of automation in general influences perceived safety of autonomous vehicles. The same kind of relation is identified between trust and perceived safety. The higher the trust in AV technology, the higher the perceived safety of autonomous vehicles.

The questions related to media influence did not yield a significant relation between media influence and perceived safety. This could indicate that media coverage of news concerning autonomous vehicles does not influence perceived safety of autonomous vehicles, regardless of it being positive or negative. However it could also mean that the survey did not contain enough respondents to generate a significant result. Another explanation has to do with a possible bias in the sample. Since a lot of the participants were in the network of TU Delft students, studying CoSEM as well, and employees of the Transport and logistics department of TNO, it could be that this group of participants is less influenced by reports about AV on the news because it is part of their study and research. So instead of basing their opinion on media coverage, it will rather be shaped by relevant scientific literature or their own research. Not one of the current behavior questions displayed a significant relation with perceived safety.

So the identified determinants of perceived safety of AV's are trust in the autonomous technology and level of automation. If during introduction of ADRT the goal would be that the perceived safety of the service needs to be of a high level, it is important to take these aspects into account. For example in the survey participants generally felt that the level 4 AV is the vehicle in which passengers would feel safest and the level 5 AV passengers would feel the least safe. In presenting the service it would therefore be advisable to use level 4 AV's in order to increase perceived safety of the service. Whether perceived safety is important for acceptance is discussed in the next sub question.

5. ***What is the relative impact of perceived AV safety on autonomous DRT acceptance, compared to other variables related to technology acceptance?***

From the results of the multiple regression analysis of the effect of the constructs derived from the UTAUT2 theory and perceived safety on behavioral intention to use ADRT, it indeed became apparent that there is a significant relation between perceived safety of AV and behavioral intention to use AV. However compared to the other constructs that were incorporated, perceived safety showed the estimate with lowest impact. Performance expectancy and effort expectancy were considered the most important constructs in accepting the technology, followed by hedonic motivation.

What influences and to what extent the acceptance of autonomous DRT services?

Generally speaking the main determinant of ADRT acceptance is travel time. This became apparent whilst comparing the estimates of travel time and travel cost of the various modes with one another. ADRT also had the highest VOTT of all the alternatives. Once again indicating that cost is somewhat less of an issue for the passengers and that there is a willingness to pay for reduced travel time. Of the constructs derived from the UTAUT2 model, Performance expectancy had the highest impact on acceptance of ADRT. Supporting this claim is that PE1 of the performance expectancy questions was related to reducing travel time.

It was hard to distinguish which of the investigated variables would follow travel time as most important. However it did become clear that effort expectancy, hedonic motivation, perceived safety, travel cost and absence of parking cost all contribute to the acceptance of ADRT services. Furthermore the identified significant determinants of perceived safety are trust in AV technology and level of automation of the vehicle.

Policy recommendations

In this section, the insights gained from the analysis of the survey are converted into relevant policy recommendations. As explained before, Autonomous vehicles and DRT services can have a positive effect on more efficient road use, emission reduction and travel safety. However, this research did not further investigate the advantages or possible disadvantages of autonomous DRT, but the determinants of ADRT acceptance in urban areas, focusing on the Dutch population. Therefore, the policy recommendations do not contain a specific advice to make (more) use of ADRT in the future, but rather give guidelines on how to increase the likelihood of acceptance when the decision to provide the service has been made.

Focus on reducing effort and increase performance

From the analysis concerning the constructs related to the UTAUT2 conceptual model, the constructs performance expectancy and effort expectancy emerged as most impactful on behavioral intention to use ADRT. From the MNL model, it became apparent that ADRT travel time has a higher impact on utility than ADRT travel cost. Since travel time also was an indicator of the construct performance expectancy, “PE1: I assume that autonomous DRT will help me save travel time”, it can be stated that the most important attribute considering ADRT acceptance is travel time.

Therefore, policymakers that want to stimulate ADRT acceptance should focus on reducing travel time in an ADRT. This can be done in numerous ways. For instance, by assigning dedicated lanes for ADRT vehicles. This doesn’t necessarily mean that an additional lane must be created, but admittance to existing bus or tram lanes could also be a viable option. Other than reducing travel time and therefore increasing performance, assigning dedicated lanes to ADRT vehicles has another advantage. This research provided evidence that perceived safety of ADRT, significantly influences possible acceptance of the service. Of the 4 perceived safety questions in the survey, the question participants had the highest average agreement on was PS-A1: "I think Autonomous DRT is not ready for public use in urban mobility". The other perceived safety questions concerned safety for other vehicles, pedestrians and travelers of the autonomous vehicle. This indicates that passengers review introducing an ADRT to the public road as the biggest safety concern amongst those alternatives. Removing the ADRT from the public road and to a dedicated lane, therefore could increase perceived safety of the service and increase the likelihood of ADRT acceptance.

Another important construct influencing ADRT acceptance is effort expectancy. The easier it is to use the service, the higher the likelihood of acceptance. However, there is no simple answer to the question on how to optimize the ease of use of the service, as this is highly dependent on the target group. If the main goal of introducing ADRT would be increasing the mobility of the elderly, a completely different strategy is needed than for instance when the goal would be to use it as a pickup service for high school children. However, it is very clear that when making sure the user experience of ordering an ADRT is easy, by reducing the amount of effort needed will have a positive effect on ADRT acceptance.

Travel times also can be reduced by having a large fleet of ADRT vehicles. This would ensure waiting times to be reduced and availability of the service to be high. However, the previously mentioned options are obviously also paired with higher investments in introducing the service to the people. This isn't necessarily a problem, since the analysis revealed that the VOTT of ADRT was the highest amongst the alternatives. This means that passengers are willing to pay more to reduce their travel time when driving an ADRT, compared to the other modes of transport incorporated in this research. Therefore when designing the optimal ADRT service, it doesn't have to be a low budget solution.

However, this obviously doesn't mean that travel costs associated with the travel service do not influence the acceptance or have no limit. The VOTT obtained in this research for ADRT is €22,57/h, which can be a guideline for the maximal travel cost versus optimal performance in order to obtain the highest acceptance.

Another less effective way of increasing acceptance of ADRT is raising parking cost for cars. The reason this is less effective is two-fold. Firstly in the MNL analysis it is observed that increased travel costs for car use have a higher impact on utility than increased parking cost. A more effective way to discourage travelers to use a car would therefore be to increase travel costs of car use, by for instance raising gasoline prices. Secondly, since there are no parking cost in the utility function of ADRT, the effect of increasing parking cost is an indirect effect. This implies that the utility of car will decrease and the utility of ADRT will stay the same when parking costs are increased and therefore ADRT utility is relatively increased compared to car. However, this goes for all the travel modes that do not have parking costs affiliated with their use. Increasing parking cost therefore can be considered an option when aiming to discourage car use, but it does not seem as the most effective way of increasing ADRT acceptance.

Improve perceived safety of AV to increase likelihood of acceptance

As mentioned before, perceived safety has a significant impact on ADRT acceptance. When compared to the constructs performance expectancy and effort expectancy, perceived safety has a lower impact on behavioral intention to use ADRT, but still was revealed as a significant variable in both the MNL as the multiple regression analysis. Therefore, enhancing the perceived safety of the service would still increase the likelihood of ADRT acceptance.

In the analysis uncovering the determinants of perceived safety, level of automation and trust in the technology arose as significant variables. Therefore, solutions to increasing perceived safety of AVs are best to be related to these subjects. Firstly, it would be advisable to start the introduction of ADRT vehicles with a level 4 autonomous vehicle. This is still a fully autonomous vehicle, but with a driver present in case of emergency. In the survey, the participants indicated that they considered a level 4 autonomous vehicle as safest option when choosing between a level 0/1/2/3, level 4 and level 5 vehicle. No additional reason was found why a level 4 vehicle is considered safer than both a level 0/1/2/3 and level 5 vehicle, but a possible explanation could be because in a level 4 vehicle there is a double security layer.

The most important determinant of perceived safety, however, is trust in AV technology. Therefore, campaigns advocating the technological and safety performance of ADRT could be a very effective tool to improve perceived safety of ADRT vehicles. Although the result of the analysis did not produce a significant relation between media influence and perceived safety. The same holds for current behavior and perceived safety.

Limitations of this research

Lack of context in the presented scenario

An often seen comment on the survey was related to the lack of more specific context in the presented scenario. A lot of participants stated that their decision is based on a lot more than time, cost and distance. The most frequently mentioned missing contextual elements were: The weather, the trip purpose, if the appointment is in your home city or an unfamiliar city, what kind of luggage do you need to carry with you, if you are in a hurry at the time of leaving and at what time during the day it is. Because of the extensive amount of travel modes and attributes, it was decided not to add anymore context related variables. However, this might have impacted the validity of the performed choices by the participants.

Hypothetical bias stated choice experiments

Inherent to stated choice experiments is the hypothetical nature of the participants answer. Contrary to revealed preference, stated preference involves asking participants for future decisions. The actual choices could therefore be different for quite a lot of reasons, e.g. because of the mentioned context scenario or unpredictability in human behavior.

Biased sample

Luckily the sample performed quite well on the test verifying the representativeness of the participants in terms of reacting to the questions related to the UTAUT2 model. These answers were compared to two studies and that seemed to indicate that the sample reacted quite similar to the Dutch population. However, the sample also differed quite a lot from the Dutch population when it came to income, level of education and age. Especially the high amount of high income individuals might have impacted the possible undervaluation of travel cost travel cost and the main focus towards travel time.

Another possible bias resulted from the way of recruiting participants for the survey. Due to the snowball sampling method a lot of participants were drawn from TU Delft and TNO, in departments related to transport and logistics. Because of the familiarity with new mobility concepts, their view on safety and performance of autonomous vehicles might be very different from a lot of other Dutch citizens.

Inflated VOTT

The first check using the general estimated parameters for travel time and travel cost generated a result close to the Dutch national average of VOTT for regular car. However when calculating with the estimates from the extended MNL model, the VOTT values were increased quite a bit. With ADRT having the highest VOTT of €22,57 and car having a value 66% above the national average. Possible explanations are the relatively big group of high income individuals and since the survey was released during a time of inflated gas prices.

Uncaptured important constructs

Quite some participant wrote in the comments section that two important motivations to choose for a travel mode were missing in the survey: Environmental friendliness and the health aspect of walking or bicycling to an appointment.

One dimensional interpretation of safety

The research as it was conducted had a somewhat one dimensional view on what safety in transport entails. In the survey, perceived safety of an ADRT was questioned as a purely technical issue. However, feeling safe in a publicly accessible small confined space could also have to do with fear of harassment. The fear of harassment could also be part of the perceived safety of a travel mode. Especially because ADRT would be a new concept where you share parts of a route with one or more strangers in a more intimate setting than a regular bus.

Recommendations for further research

This research contributed to enhancing the validity of TNO's NMM. By collecting stated choice data, it became possible to estimate parameters based on actual data, instead of making assumptions based on theory and previous models. The influence of several attributes of new modes, such as ADRT, can be used in the model, which uses these parameters for further analysis on modal split, traffic intensities etc.

It has also added to the state of the art in academic research by exploring the variables that influence the acceptance of autonomous DRT in urban areas. Amongst travel time and travel costs confirming that perceived safety indeed is a significant parameter in accepting ADRT as a new form of transport. However, the explanation on the determinants of perceived safety fell somewhat short. Using a more complex definition of urban travel safety of ADRT, compared to the one-dimensional focus on technical safety used in this research, could result in a deeper understanding of ADRT perceived safety determinants. This could add on the knowledge on what can make ADRT be perceived as safe.

Another recommendation would be to collect data from a more representative sample in terms of age, income, level of education, since the socio demographic characteristics in the current one are not representative of the Dutch population. Also, a larger group of participants could form a solid basis for more reliable model results, as well as a more advanced modeling method such as a Structural Equation Model (SEM).

Another option for expanding the knowledge on the acceptance of ADRTs could be to look into the contextual variables that had been omitted from this survey, especially since the participants stressed that this could be important in their decision making process. The weather, the trip purpose, if the appointment is in your home city or an unfamiliar city, what kind of luggage do you need to carry with you, if you are in a hurry at the time of leaving and at what time during the day it is. Incorporating contextual variables like this could result in a better understanding of choice behavior and more realistic estimation of mode choice by travelers.

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Appendix

Appendix A Survey introduction

“This survey consists of 3 parts. In the first part you are asked to make a choice between several travel options to complete a fictional trip. In the second part you have to indicate to what degree you agree with several statements about a new form of travelling. And the last part contains some conclusive questions.

On the next page some additional information about the first assignment will be provided.

In the first part of this survey you are asked to think about the following fictional travel scenario:

You have an appointment in a city. At the moment of departure you are already in that same city and the distance to your appointment is 5 kilometers. You will travel to this destination and will stay on that location for approximately 2 hours. After the appointment you will leave this location and resume your day.

To complete this trip, you are asked to make a choice between 5 different travel modes (More information on travel modes will be given on the next page).

All of the travel modes have several features that will be changed in every question (More information on the features will be given on the next page).

Information about the available travel modes

Car: In this research when "car" is mentioned we talk about a standard privately owned car.

Public Transport: In this research we mean inner city transport like buses, trams and metro that are available to the public, charge set fares, and run on fixed routes.

Shared Bicycle: The Bicycle is well known in the Netherlands. In this research we talk about a shared bicycle. This means you will need to pay a fee to make use of the bicycle and you will need to walk to a pick up point.

Autonomous DRT: In the future, new forms of transportation will become available. One of these new forms of transportation could be DRT (Demand Responsive Transport). DRT is a form of shared transportation. Passengers can order a DRT to pick them up at a desired location and drop them of at a specific destination. A DRT vehicle usually looks like a small van that has capacity for 6-8 passengers. During a ride with a DRT, the vehicle will make several stops to drop off and pick up passengers.

This research focuses on Autonomous DRT. That means that the DRT vehicle is completely self-driving without a human driver present.

A picture of what an Autonomous DRT could look like is shown below.

Example of Autonomous DRT exterior (source: Canada motor jobs)

Example of Autonomous DRT Interior (source: Canada motor jobs)

Shared car: A shared car is a vehicle that can be rented via an application for a short time period in order to reach a desired destination. When using a shared car you pay for the amount of minutes driving the car or the distance driven with the car. In this research we consider a car sharing concept, where you can pick up the car at a certain location and drop it of somewhere near your destination. The user of the car does not have to pay parking cost and only pays the renting costs of the vehicle.

Information about the features of the travel modes:

Travel time: The amount of minutes spent in/on a certain mode of transportation in order to reach the destination. Applies to all the different travel modes.

Access & egress time: Access time is the amount of minutes spent walking from your original location to the entry point of the mode of transportation. Egress time is the amount of minutes spent walking from the stop of the mode of transportation to your final destination.

Waiting time: The time you have to wait before you can enter the mode of transportation. For instance the time spent waiting at the public transport stop. This only applies to Public transport and Autonomous DRT.

Travel cost: The costs associated with using a certain mode of transportation. For instance the price of a bus ticket or the fare price of an autonomous DRT.

Parking cost: The cost of parking at a certain location. Only applies to the travel mode "Car".

Only the features that apply to a certain travel mode will have a value. For instance: There is no parking cost when you would travel with “public transportation”, this only applies to the travel mode “car”.

Although the distance in every scenario is the same, the features of the travel mode will change in every question. Same as in a real situation, travel times or waiting times can be affected by congestion, road blocks or other variables. Prices can differ due to rising gasoline prices, inflation or new government regulations. This is why the value of the features differs in every question.”

Appendix B Ngene code, SCE final design and MNL output

Code Ngene:

Design

;alts = Car, Public transport, Bicycle, Autonomous DRT, Shared car

;rows = 9

;eff = (mnl,d)

;model:

U(Car) = C + Tt[-0.1679]*Travel Time_car[12,15,20]+ Tc[-0.1978]*Travel cost_Car[2.50,3.20,4.30]+Pc[-0.2882]*Parking cost_car[4,5,7]+ Ae[-0.2620]*Access and egress time[2,5,10] /

U(Public transport) = Tt[-0.1679]*Travel Time_pt[14,18,24]+ Tc[-0.1978]*Travel cost_pt[1.90,2.40,3.20]+ Wt[-0.1647]*Waiting time[2,5,10] + Ae[-0.2620]*Access and egress time[2,5,10] /

U(Bicycle) = Tt[-0.1679]*Travel Time_bi[18,24,30] + Tc[-0.1978]*Travel cost_bi[1.90,2.40,3.20] + Ae[-0.2620]*Access and egress time[2,5,10] /

U(Autonomous DRT) = Tt[-0.1679]*Travel Time_adrt[14,18,24]+ Tc[-0.1978]*Travel cost_Adrt[2.50,3.20,4.30]+ Wt[-0.1647]*Waiting time[2,5,10] /

U(Shared car) = Tt[-0.1679]*Travel Time_sc[12,15,20]+ Tc[-0.1978]*Travel cost_sc[3.40,4.30,5.80]+ Ae[-0.2620]*Access and egress time[2,5,10]

$

Stated choice experiment

Question 1

	Car	**Public transport (bus, tram metro)**	**Shared Bicycle**	**Autonomous DRT**	**Shared car**
Travel time	20 min	24 min	30 min	18 min	12 min
Access & egress time	10 min	10 min	2 min	0 min	10 min
Waiting time	0 min	2 min	0 min	10 min	0 min
Travel cost	€3,20	€3,20	€1,90	€4,30	€3,40
Total Parking cost	€5	€0	€0	€0	€0

Question 2

	Car	Public transport (bus, tram metro)	Shared Bicycle	Autonomous DRT	Shared car
Travel time	15 min	24 min	24 min	24 min	12 min
Access & egress time	2 min	5 min	5 min	0 min	5 min
Waiting time	0 min	5 min	0 min	2 min	0 min
Travel cost	€4,30	€2,40	€3,20	€3,20	€3,40
Total Parking cost	€4	€0	€0	€0	€0

Question 3

	Car	Public transport (bus, tram metro)	Shared Bicycle	Autonomous DRT	Shared car
Travel time	15 min	18 min	24 min	18 min	15 min
Access & egress time	5 min	5 min	5 min	0 min	10 min

Waiting time	0 min	5 min	0 min	2 min	0 min
Travel cost	€4,30	€3,20	€3,20	€2,50	€4,30
Total Parking cost	€5	€0	€0	€0	€0

Question 4

	Car	**Public transport (bus, tram metro)**	**Shared Bicycle**	**Autonomous DRT**	**Shared car**
Travel time	15 min	14 min	18 min	24 min	20 min
Access & egress time	5 min	2 min	10 min	0 min	2 min
Waiting time	0 min	10 min	0 min	5 min	0 min
Travel cost	€2,50	€1,90	€1,90	€3,20	€5,80
Total Parking cost	€7	€0	€0	€0	€0

Question 5

	Car	Public transport (bus, tram metro)	Shared Bicycle	Autonomous DRT	Shared car
Travel time	20 min	24 min	18 min	14 min	15 min
Access & egress time	10 min	2 min	10 min	0 min	2 min
Waiting time	0 min	2 min	0 min	5 min	0 min
Travel cost	€3,20	€1,90	€2,40	€2,50	€5,80
Total Parking cost	€5	€0	€0	€0	€0

Question 6

	Car	Public transport (bus, tram metro)	Shared Bicycle	Autonomous DRT	Shared car
Travel time	12 min	18 min	30 min	18 min	12 min
Access & egress time	5 min	10 min	2 min	0 min	10 min

Waiting time	0 min	5 min	0 min	10 min	0 min
Travel cost	€4,30	€2,40	€1,90	€4,30	€3,40
Total Parking cost	€7	€0	€0	€0	€0

Question 7

	Car	**Public transport (bus, tram metro)**	**Shared Bicycle**	**Autonomous DRT**	**Shared car**
Travel time	12 min	14 min	18 min	24 min	15 min
Access & egress time	2 min	5 min	10 min	0 min	5 min
Waiting time	0 min	10 min	0 min	5 min	0 min
Travel cost	€2,50	€1,90	€2,40	€3,20	€5,80
Total Parking cost	€7	€0	€0	€0	€0

Question 8

	Car	Public transport (bus, tram metro)	Shared Bicycle	Autonomous DRT	Shared car
Travel time	20 min	14 min	24 min	14 min	20 min
Access & egress time	10 min	2 min	5 min	0 min	2 min
Waiting time	0 min	10 min	0 min	2 min	0 min
Travel cost	€3,20	€3,20	€3,20	€2,50	€3,40
Total Parking cost	€5	€0	€0	€0	€0

Question 9

	Car	Public transport (bus, tram metro)	Shared Bicycle	Autonomous DRT	Shared car
Travel time	12 min	18 min	30 min	14 min	20 min
Access & egress time	4 min	10 min	2 min	0 min	5 min

Waiting time	0 min	2 min	0 min	10 min	0 min
Travel cost	€2,50	€2,40	€2,40	€4,30	€4,30
Total Parking cost	€4	€0	€0	€0	€0

NL translation:

Question 1

	Auto	**Openbaar vervoer (bus, tram metro)**	**Deelfiets**	**Autonome DRT**	**Deelauto**
Reistijd	20 min	24 min	30 min	18 min	12 min
Toegangs- en uitstaptijd	10 min	10 min	2 min	0 min	10 min
Wachttijd	0 min	2 min	0 min	10 min	0 min
Reiskosten	€3,20	€3,20	€1,90	€4,30	€3,40
Parkeerkosten	€5	€0	€0	€0	€0

Question 2

	Auto	Openbaar vervoer (bus, tram metro)	Deelfiets	Autonome DRT	Deelauto
Reistijd	15 min	24 min	24 min	24 min	12 min
Toegangs- en uitstaptijd	2 min	5 min	5 min	0 min	5 min
Wachttijd	0 min	5 min	0 min	2 min	0 min
Reiskosten	€4,30	€2,40	€3,20	€3,20	€3,40
Parkeerkosten	€4	€0	€0	€0	€0

Question 3

	Auto	Openbaar vervoer (bus, tram metro)	Deelfiets	Autonome DRT	Deelauto
Reistijd	15 min	18 min	24 min	18 min	15 min
Toegangs- en uitstaptijd	5 min	5 min	5 min	0 min	10 min

Wachttijd	0 min	5 min	0 min	2 min	0 min
Reiskosten	€4,30	€3,20	€3,20	€2,50	€4,30
Parkeerkosten	€5	€0	€0	€0	€0

Question 4

	Auto	**Openbaar vervoer (bus, tram metro)**	**Deelfiets**	**Autonome DRT**	**Deelauto**
Reistijd	15 min	14 min	18 min	24 min	20 min
Toegangs- en uitstaptijd	5 min	2 min	10 min	0 min	2 min
Wachttijd	0 min	10 min	0 min	5 min	0 min
Reiskosten	€2,50	€1,90	€1,90	€3,20	€5,80
Parkeerkosten	€7	€0	€0	€0	€0

Question 5

	Auto	Openbaar vervoer (bus, tram metro)	Deelfiets	Autonome DRT	Deelauto
Reistijd	20 min	24 min	18 min	14 min	15 min
Toegangs- en uitstaptijd	10 min	2 min	10 min	0 min	2 min
Wachttijd	0 min	2 min	0 min	5 min	0 min
Reiskosten	€3,20	€1,90	€2,40	€2,50	€5,80
Parkeerkosten	€5	€0	€0	€0	€0

Question 6

	Auto	Openbaar vervoer (bus, tram metro)	Deelfiets	Autonome DRT	Deelauto
Reistijd	12 min	18 min	30 min	18 min	12 min
Toegangs- en uitstaptijd	5 min	10 min	2 min	0 min	10 min

Wachttijd	0 min	5 min	0 min	10 min	0 min
Reiskosten	€4,30	€2,40	€1,90	€4,30	€3,40
Parkeerkosten	€7	€0	€0	€0	€0

Question 7

	Auto	**Openbaar vervoer (bus, tram metro)**	**Deelfiets**	**Autonome DRT**	**Deelauto**
Reistijd	12 min	14 min	18 min	24 min	15 min
Toegangs- en uitstaptijd	2 min	5 min	10 min	0 min	5 min
Wachttijd	0 min	10 min	0 min	5 min	0 min
Reiskosten	€2,50	€1,90	€2,40	€3,20	€5,80
Parkeerkosten	€7	€0	€0	€0	€0

Question 8

	Auto	Openbaar vervoer (bus, tram metro)	Deelfiets	Autonome DRT	Deelauto
Reistijd	20 min	14 min	24 min	14 min	20 min
Toegangs- en uitstaptijd	10 min	2 min	5 min	0 min	2 min
Wachttijd	0 min	10 min	0 min	2 min	0 min
Reiskosten	€3,20	€3,20	€3,20	€2,50	€3,40
Parkeerkosten	€5	€0	€0	€0	€0

Question 9

	Auto	Openbaar vervoer (bus, tram metro)	Deelfiets	Autonome DRT	Deelauto
Reistijd	12 min	18 min	30 min	14 min	20 min

Toegangs- en uitstaptijd	4 min	10 min	2 min	0 min	5 min
Wachttijd	0 min	2 min	0 min	10 min	0 min
Reiskosten	€2,50	€2,40	€2,40	€4,30	€4,30
Parkeerkosten	€4	€0	€0	€0	€0

Appendix C Apollo MNL code generic attributes

```
### Load Apollo library

library(apollo)

### Initialise code

apollo_initialise()

### Set core controls

apollo_control = list(

  modelName  ="MNL_1",

  modelDescr ="MNL model Ruben Knipscheer final survey",

  indivID    ="ID"

)

#### LOAD DATA

database = read.table("Data final survey MNL RK 2022.dat",header=TRUE)

### Vector of parameters, including any that are kept fixed in estimation

apollo_beta=c(BETA_TT   = 0,

              BETA_AE   = 0,

              BETA_W  = 0,
```

```
        BETA_TC   = 0,

        BETA_PC = 0)

### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta,
use apollo_beta_fixed = c() if none

apollo_fixed = c()

#### GROUP AND VALIDATE INPUTS

apollo_inputs = apollo_validateInputs()

#### DEFINE MODEL AND LIKELIHOOD FUNCTION

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

 ### Attach inputs and detach after function exit

 apollo_attach(apollo_beta, apollo_inputs)

 on.exit(apollo_detach(apollo_beta, apollo_inputs))

 ### Create list of probabilities P

 P = list()

 ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant

 V = list()

  V[['Car']]  = TT_CAR * BETA_TT + AE_CAR * BETA_AE + TC_CAR * BETA_TC + PC_CAR * BETA_PC

  V[['Public transport']]  = TT_PT * BETA_TT + AE_PT * BETA_AE + W_PT * BETA_W + TC_PT * BETA_TC

  V[['Bicycle']]  = TT_BIC * BETA_TT + AE_BIC * BETA_AE + TC_BIC * BETA_TC

  V[['Autonomous DRT']] = TT_ADRT * BETA_TT + W_ADRT * BETA_W + TC_ADRT * BETA_TC

  V[['Shared car']] = TT_SC * BETA_TT + AE_SC * BETA_AE + TC_SC * BETA_TC

  ### Define settings for MNL model component

  mnl_settings = list(

   alternatives  = c("Car"=1, "Public transport"=2, "Bicycle"=3, "Autonomous DRT"=4, "Shared car"=5),

   avail        = list("Car"=1, "Public transport"=1, "Bicycle"=1, "Autonomous DRT"=1, "Shared car"=1),

   choiceVar     = CHOICE,
```

```
    V          = V
   )

  ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)
  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)
  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
#### MODEL ESTIMATION
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)
#### MODEL OUTPUTS
apollo_modelOutput(model,modelOutput_settings=list(printPVal=TRUE))
apollo_saveOutput(model)
```