Safety assessment of the interaction between an automated vehicle and a cyclist

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Master Thesis
Transport, Infrastructure & Logistics
TUDelft | 2019

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Graduation Report

Delft University of Technology

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MSc Transport, Infrastructure and Logistics

December 2019 | Delft, Netherlands

MSc Thesis in Transport, Infrastructure and Logistics – Graduation Report

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December 2019

Acknowledgments

I have always been curious about transport innovations, but the concept of automated vehicles makes me passionate. Besides the fact that I worked on a topic that I am excited about, this research is even more special for me, as I see that the outcomes of my work are of practical interest. This report is the outcome of seven months of hard work, the fulfillment of this study would not be possible without the underlying people.

I want to share my gratitude to the entire thesis committee. To professor Bart van Arem who was first to introduce to me the automated vehicles and keep supporting me in the most important points of my study. Thank you for being the light during the toughest moments. To Haneen Farah, for always being there for me with endless enthusiasm and generous support. I could not have imagined having a better advisor and mentor. To Peter Morsink and Shubham Bhusari who trusted me endlessly and gave freedom to express myself in the research. Thank you Peter for constructive comments and funny jokes. Thank you Shubham for supporting me with every small bit and at any time when I needed you: with my first interview, on the field test, during all meetings and at my final presentation. To Riender Happee for the straight to a point advises and warm encouragement on the meetings both at university and with the I-AT project authorities. Thank you all for challenging me and making this journey transformational for me.

I am deeply grateful to people without whom the experiment will not take place. To Edwin Scharp, Peter van Oossanen, Paul van Gent for their help in equipping the vehicle and a bicycle; in conducting an experiment and in processing data. To Freddy Antony Mullakkal Babu for explaining and discussing with me every small detail of your safety algorithm. To Nagarjun Reddy for helping me with processing the park management permission. To Shubham Bhusari, Marcelo Matias and Xiaodong Luo for helping with the experiment. Warm thanks for everyone who took part in the experiment as participants.

Thanks to all my friends, the one I met before starting my studies in Delft and the one I met in Netherlands. The very special gratitude to my housemates, who make me feel home: Camille, Adrien, Rocio and Monica. A huge thank you to Marcelo and Luo for sharing with me so much happiness and for always been my support. A special thank you to Varvara, a friend that I know half of life, thank you for this very special connection that we have.

I was extremely lucky to meet my best friends in the first seconds of my life. The deepest gratitude to my mother Tatyana and my father Ilya – you are everything for me. You teach me the importance of high goals and hard work. Thank you for giving me strength in downs and sharing the joy of all ups of my research. For all your support and love, I sincerely thank you.

Filled, I am finishing the journey in the delft university with this inspiring research. Dear reader, at this point I am proud to share my work.

Oskina Maria,
Delft, December 2019

Abstract

The operation of automated vehicles in shared areas requires attention with respect to the interaction between AVs and vulnerable road users, including cyclists. Currently, the programmed interaction behavior of AVs is based on the knowledge of the interaction between conventional vehicles and cyclists. However, cyclists may react differently to conventional and automated vehicles. Therefore, this research applies field test experiment to investigate the risks resulting from the interaction between cyclist and an AV. Four possible interaction scenarios were investigated in within-subject design with overtaking speed, overtaking distance and right-hand side objects as attributes. Objective Risk is assessed using the Probabilistic Driving Risk Field and Subjective Risk is assessed based on the self-reported values, cyclist behavior and trust. Results show that in general following has less risk than overtaking. Automated following and manual following have the same level of Objective and Subjective risks, while the automated overtaking has higher risks than manual overtaking. However, results also show that a larger interaction time leads to an increase in cycling speed and decrease in the distance to the curb. Furthermore, in the following maneuver the interaction time is higher than in the overtaking maneuver. Besides high time of interaction, closer overtaking distance and green grass on the right-hand side affect the increase in subjective and objective risks.

Keyword: •Automated Vehicle •Vulnerable Road Users •Subjective Risk •Objective Risk

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List of Abbreviations

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance System
AV	Automated Vehicle
ASB	Automated Shuttle Bus
GPS	The Global Positioning System
Lidar	Light Detection and Ranging
I-AT	Interregional Automated Transport
ODD	Operation Design Domain
PDRF	Probabilistic Driving Risk Field
PDSF	Probabilistic Driving Safety Field
RHS	Right Hand Side
SMoS	Surrogate Measures of Safety
VRU	Vulnerable Road Users

1 Introduction

1.1 Background and motivation

The last decades have shown a stable growth of the amount of sold cars in the transport industry. In addition to the environmental issues associated with emissions of petrol cars, the increased number of cars in use causes traffic congestion and traffic accidents. The U.S. Department of Transportation reported that in 2017 a total of 53 million motor vehicles were involved in traffic accidents and these crashes resulted in 37 million deaths (Kahn & Gotschall, 2015). For 26% of crashes the major influencing factor was speed and other contributing main factors are alcohol and lack of use of safety belt. These three contributing factors are related to drivers' behavior (Kahn & Gotschall, 2015). Automated Vehicles (AVs) are a potential solution to increase traffic safety. AVs are designed to replace human drivers in some (or all) of the driving tasks. The Society of Automotive Engineers (SAE, 2016) defined six levels of automation. Depending on the level of automation, the vehicle controls some of the driving tasks, such as the driving speed (longitudinal dimension) or the lane positioning (lateral dimension), or all of the driving tasks – i.e. the automated system can perform the whole driving process without any human involvement (GHSA, 2018).

On the road, road users are constantly in the process of interaction. The interaction process between two human drivers would include both explicit and implicit communication channels. Vehicle drivers can share their intentions explicitly with turning signals and backup lights. This kind of interaction is possible as well for automated system. Drivers can also share intention implicitly with the glance direction and position in lane change. This kind of interaction, however, is currently not possible to be processed by the automated vehicle. Non-motorized modes of transport, namely cyclists and pedestrians, mostly use implicit communication channels when interacting with other road users. Human vehicle drivers mostly use gestures and eye contact to show non-motorized road users their intentions (Lagstrom & Lundgren, 2015). The investigation on the interaction process between AVs and VRUs enables to conclude on the best interaction strategy. Additional importance of the research comes from the fact that VRU user group are the least protected. To prevent misunderstanding in communication between AVs and VRUs, AV's are currently programmed in a way to minimize their interactions with vulnerable road users. In interaction with pedestrians, an AV is programmed to stop, which corresponds to the behavior of the human driver. In interaction with the cyclist, one of the possible programmed behavior for the AV is to follow the bicycles at rider speed (I-AT, 2019). Such a behavioral approach is not efficient in terms of traffic operation performance. In addition, cyclists may perceive being followed by a vehicle as dangerous.

To design a reliable communication process between AVs and vulnerable road users (VRUs), it is necessary to investigate how pedestrians and cyclists estimate risk level caused by the AVs. Previous studies investigated ways for safe communication between AVs and non-motorized road users, especially pedestrians (Böckle, Brenden, Klingegård, Habibovic, & Bout, 2017; Lagstrom & Lundgren, 2015; Merat, Madigan, & Nordhoff, 2017). There are very few studies focusing on the interactions between cyclists and AVs. One study used a photo experiment to study the interactions between AVs and cyclists, however the results of the research were not statistically significant (Hagenzieker et al., 2018). Even though pedestrians and cyclists are both non-motorized modes of transport and may have similarities in their behavior, cyclists still have specific behavioral features. It is important to investigate how cyclists react on different automated vehicles actions and which AV behaviors result in the highest safety of interactions.

1.2 Scientific relevance and research gap

Transport safety is influenced by technical and human factors. Automated vehicles can solve safety issues related to the speeding. However, it remains a challenge to maintain a direct communication between automated vehicles and other road users. At an early stage of development of vehicle automation, the interaction process was investigated from the perspective of an automated vehicle. Studies on the processes of the automated vehicle detection and reaction to other road users were of great interest. Researchers also have shown interest in user reactions to automated vehicle on motorways. In recent years, automated vehicles have appeared on shared roads. Currently, research is mainly conducted on the interaction of pedestrians and AVs.

Lagstrom & Lundgren (2015) show that pedestrians feel more insecure when interacting with AV if they can't fully interpret AV behavior. In such situations, pedestrians tend to be willing to wait until the vehicle stops or until they are sure which actions the AV is taking. Rodriguez Palmeiro et al. (2017) shows that pedestrians reported generally feeling less safe and behave more cautious when interacting with AVs. The same result was reported by Böckle et al., 2017; Habibovic et al., 2018; Merat et al., 2017. Decreased confidence in automated vehicle technology may affect pedestrian interaction behavior and general willingness to interact with AV. Böckle et al., 2017; Habibovic et al., 2018; Merat et al., 2017 reported that vulnerable road users differ in behavior when interacting with an automated vehicle from the behavior that people show when interacting with conventional vehicles.

One of the main features of automated driving is the ability for the human driver to not be fully involved in the driving process. However, Lagstrom & Lundgren (2015) found that most participants in the experiment did not want to cross if the human driver inside automated vehicle was distracted. In the Rodríguez Palmeiro et al. (2018) study, 95% of participants reported that driver inattention affects their perceived safety level and the decision to cross. To increase cyclist's awareness of automated vehicle operations and to facilitate communication process between an AV and a pedestrian, researchers offer various communication tools for automated vehicles. These tools should allow an automated vehicle to clearly express its intentions (Böckle et al., 2017; Lagstrom & Lundgren, 2015; Merat et al., 2017).

The interaction of AV with a pedestrian is a topic of great interest. However, the interaction between the cyclist and AV is not well researched. Hagenzieker et al. (2018) conducted a questionnaire study on the behavior of cyclists. During the experiments, participants were asked to study photos of automated vehicle and conventional vehicles with different signs. The purpose of the research was to investigate if the cyclist could correctly interpret when automated vehicles noticed them and whether an automated vehicle would stop for them. Researches show that the cyclist interacted more confidently with conventional vehicles than with automated ones (Hagenzieker et al., 2018). The lack of interest of researchers in the study of the interaction between the cyclist and automated vehicles can be explained by the similarity in the behavior of vulnerable road users. However, cyclist have more interaction scenarios with AVs than pedestrians, for example sharing carriageways with AVs.

The current approach that AVs interacting with cyclists is to follow the cyclist with the same speed and to perform a controlled automatic stop or overtaking in manual mode. Overtaking and passing maneuvers on two-lane roads (one lane per travel direction) are seen as high-risk level. While performing overcoming the driver must be sure that there is sufficient gap space in front of the bicycle for the vehicle to return to the driving line. At the same time, it should be verified that there is enough time gap before vehicle on the opposing lane direction appears (Cavadas, Azevedo, Farah, & Ferreira, 2018). Such overtaking maneuvers can be dangerous for the bicycle drivers, which have no physical protection. At the same time, requirements to follow bicycles on the shared roads are inefficient for following traffic situation and may also have negative reaction from the cyclist, especially due to recent nature of the automated vehicles technologies.

Cyclists may react to vehicles in a different, sometimes even inadequately way (Hagenzieker et al., 2018). The behavior of the automated vehicles has been programmed based on the data obtained from research on vehicle – cyclist interaction. However, cyclist may behave differently in the interaction with the automated vehicle (Hagenzieker et al., 2018). It may be needed to correct the programmed behavior of the automated vehicle. To propose a new behavior for the AVs, the risk level of the interaction scenarios has to be assessed both from the point of view of objective risk and subjective risk level. In the end run possibilities may be illuminated for the longer automated vehicles run scenarios. However, so far almost no researches were conducted to assess cyclist subjective risk level in the interaction with automated vehicle. The master thesis research is aiming to fulfill this research gap. Research on the cyclist behavior is especially relevant in the contest of the Netherlands, where amount of cyclist and cyclist trips are one of the highest in Europe, with a modal share of 36% (Oakil, Ettema, Arentze, & Timmermans, 2016).

Additionally, a novel safety risk metric will be used to assess the objective risk level of interaction. An advantage of the novel safety metric is its ability to show the level of risk of a situation that does not directly cause an accident. In the research the novel risk metric will be used for the first time to assess the risk caused by the interaction with dynamic objects in the field-experiment.

Due to all the above-mentioned research gaps, the present research will focus on analyzing the reaction of the cyclist on the interactions with automated vehicle. During the study, the new safety metric will evaluate the objective level of risk for various interaction scenarios.

1.3 Relevance for the I-AT project

The master thesis research is part of the Interregional Automated Transport (I-AT) research project. During the project it is intended to drive with the new semi-automated shuttle bus in the region between Vaals and Aachen. The general aim of the I-AT project is to examine the feasibility of this system.

To answer the main research question of I-AT project, the route assessment protocol is being developed. Currently, the first stage of the protocol has been finished. The next step of the route assessment protocol should be related to the interaction with other road users. Besides following the pre-defined path, the automated shuttle must also safely and efficiently react to other road users. The Vaals-Aachen route must be re-examined to investigate on which parts of the route automated driving is possible in terms of possible interaction scenarios. Using the example of cyclist-AV interaction the research proposes a methodology that can be used in the next stage of the assessment protocol. The master thesis research will provide direction which interaction scenarios are possible for automated operation and which actions an automated shuttle bus should take when performing a certain interaction scenario. The master thesis research proposes to decide actions of the automated shuttle bus based on the risk level of interaction. In the interaction between cyclist and automated shuttle bus, cyclist is more vulnerable subject. Following that, risk level must be perceived from his side. The Automated Shuttle Bus has to correct actions based on the risk level of cyclist.

Besides building an assessment protocol, the results of the thesis research can be directly used in the driver's manual document to increase the awareness of human drivers of the impact of an automated shuttle bus actions on the interaction risk levels.

1.4 Research objective and questions

An interaction process between an automated vehicle and a cyclist is characterized by a subjective risk and objective risk. Subjective Risk is a risk perceived by cyclist and Objective Risk is a risk calculated based on the data from the experiment. Different operation condition requires different behavior from the vehicle. Vehicle behavior is presented in the interaction scenario by the mode of the vehicle and vehicle maneuver. The main objective of this study is to research and give recommendations on the interaction scenario resulting in the minimal Objective and Subjective Risks. Taking in the account the scientific and practical gaps and the objective of this study, the research question can be formulated as follows:

RQ: *Which interaction scenario minimizes Subjective and Objective Risks appearing when an automated vehicle approaches a cyclist from behind?*

The main research question includes the following sub questions:

SQ 1: *Which interaction scenarios are possible when an automated vehicle approaches a cyclist from behind?*

SQ 2: *What is the cyclist subjective risk level for the interaction scenarios?*

SQ 3: *What is the objective risk level for the interaction scenarios?*

SQ 4: *What are possible solutions to lower subjective and objective risk levels in the interaction scenarios?*

1.5 Research approach

This section gives an overview of steps that the methodology composed of (Figure 1), the detailed description of the methodology analyses is provided in the Chapter 3.

The first step relates to the looking at the background of the research, defining the promising interaction scenarios and corresponding to them interaction attributes. The first step answers the 1st research sub question. During the first step the Literature Research and Consultation of experts were applied. The consultation of experts stands for the discussions with the professionals from the I-AT project. The final interaction scenarios were defined based on the scientific and practical relevance.

The next step corresponds to the data collection method using a real-case experiment. The interaction scenarios and attributes chosen on the previous steps give an input for designing the experiment scenarios. Questionnaires were used to collect data for Subjective Risk and sensors on the vehicle and bicycle were used to collect data for Objective Risk. After the experiment was designed and organized, including choosing the experiment location, recruiting participants and receiving permissions from the Ethical Committee and Park management Delft, the pilot-experiment was conducted. Pilot-experiment supports the choice of the most promising experiment attributes and shows the point of improvements in the overall experiment organization.

On the third step all input data was processed. The accuracy was checked using the measurements made during the field test. Next, the data was filtered: the participants rides were selected out of all captured data with the use of the geo-fence method and the overtaking moments were selected with the use of the video data.

All processed data was used as an input for the data analysis. The objective Risk was calculated using the Probabilistic Driving Risk Field (PDRF) safety algorithm. The trust level was also recalculated from the answers on 12 questions to the 1 value. Next data analysis was conducted, and the first results drawn.

Results were discussed and compared to the findings from the literature review. On the step 5 the key findings, answering the research sub-questions 2,3 and 4, were reported and conclusion on the main thesis research question drawn. On the last step it was reflected how the findings of the research contribute to the scientific gap and which practical application of the conclusions is possible for the I-AT project.

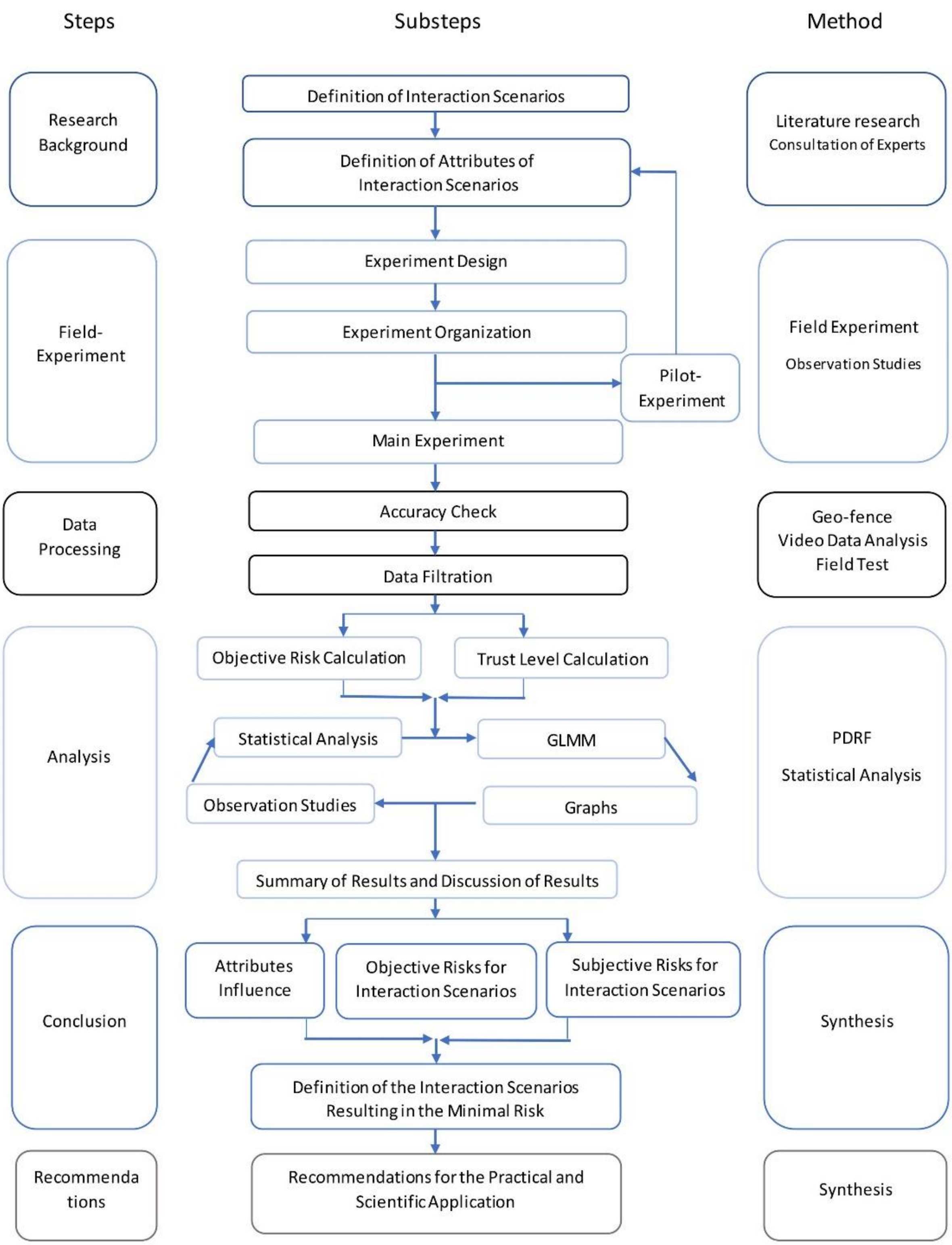


Figure 1: Research approach

1.6 Research scope

- The master thesis research is part of the I-AT project. Interaction scenarios between the vehicle and the cyclist were selected when relevance to the I-AT operation route. Thus, master thesis research considers only following and accelerative overtaking scenarios.
- The choice of the attributes and the number of levels of each attribute were limited due to time constraints. Thus, only 3 attributes were included with 2 levels each.
- The experiment includes only students recruited at the TU Delft university. Participants may have a higher level of knowledge about automated vehicles than the average cyclist and show higher trust level for AVs. Besides that, the experiment includes 25 participants, and only 10 participants data were used for the Objective Risk calculation.
- The questionnaire did not include questions on the sensation seeking level of cyclists, due to the large number of questions, and did not include questions on the cycling level, due to the restriction from the TU Delft Ethical Committee.
- The master thesis research experiment is a controlled experiment. To maintain the necessary level of safety during the experiment, the road of the experiment was blocked from the traffic. Thus, the traffic situation has limited realism.

2 Literature research

Automated vehicles (AV) currently present on the road still require driver intervention. Transition of control mostly happen due to the AV safety threat from other road users. To increase awareness of the driving situations that require human driver control, the interaction process between AVs and other road users must be examined. One of the interaction scenarios include the overtaking maneuvers.

2.1 Overtaking maneuvers

Overtaking maneuver consists of different stages. Shamir (2004) identified three steps in the overtaking diverting from the lane, driving straight in the adjacent lane and returning to the lane. In contrast, Dozza, Schindler, Bianchi-Piccinini, & Karlsson (2016) identified four overtaking phases. The illustration of the four stages is performed in the Figure 2: Overtaking maneuver phases (Dozza et al., 2016a)Figure 2.

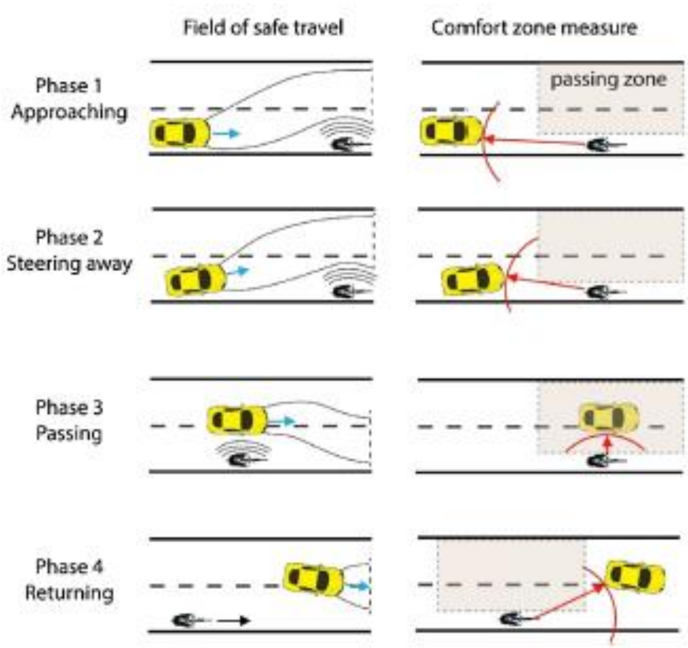


Figure 2: Overtaking maneuver phases (Dozza et al., 2016a)

According to Dozza et al., (2016), in the first phase the motorized vehicle reaches the bicycle from behind. The next phase begins when the driver starts to steer away to reach the overtaking lane. When the driver reaches the passing zone, the passing phase begins. As soon as the driver overtook the cyclist, the return phase starts. At the return phase, the vehicle returns to the original lane in front of the bicycle. In the master thesis research, the first stage (approach stage) will not be applied. In scenarios, overtaking occurs after the following operations. Thus, the automated shuttle bus will first follow the cyclist and then begin to overtaking right from the second phase (steering away). Also, the master thesis research does not consider the return stage. It is assumed that the experiment will capture the risk of overtaking already at the stage of passing.

At the phase of passing, the driver of the vehicle chooses a certain distance of passage. This distance is one of the parameters that can have a potential impact on the level of overtaking risk, as this distance defines the trajectory of overtaking. Research from Weddell (2012) shows that the distance of passing depends on the speed of the overtaking vehicle, the presence of an oncoming traffic, the size of the overtaking vehicle, the distance of the cyclist to the curb and the width of the bicycle lane.

2.1.1 Speed.

Literature shows a correlation between the speed of an overtaking vehicle and the distance that drivers keep to the cyclist. Research of Parkin & Schackel (2014) shows that for a vehicle with a speed of about 45 km/h, the average passing distance is 1,6 m. A similar result is retrieved from the experiment of Debnath, Haworth, Schramm, Heesch, & Somoray (2018), in which the mean passing distance for driving at 40 km/h was 1,5 m, for 60 km/h – 2 m and for 70 km/h – 2,4 m. Dozza et al., (2016) found that the boundaries of the comfort zone are 2.03±0.28m in size at a vehicle speed of 80 km/h. Besides the comfortable passing distance, there is also accepted passing distance. Parkin & Meyers (2010) show that at a speed of 48 km/h, drivers accepts to overtake a cyclist with a distance of 1.05 meters.

2.1.2 Distance of cyclist to right-hand side objects.

Another parameter influencing the vehicle passing distance is a distance that a cyclist chooses to keep from right hand side objects. Research by Weddell (2012) shows that the further cyclists drive from the curb the smaller was the passing distance of the overtaking motorized vehicles, including scenarios with a bicycle lane. Walker (2007) confirms this result, finding that there is an interrelation between the riding position of the cyclist and the distance that drivers prefer to keep when overtake a cyclist. If the cyclist rides with a 0,25 m distance from the curb, drivers chose to overtake with a distance of 1,47 m.

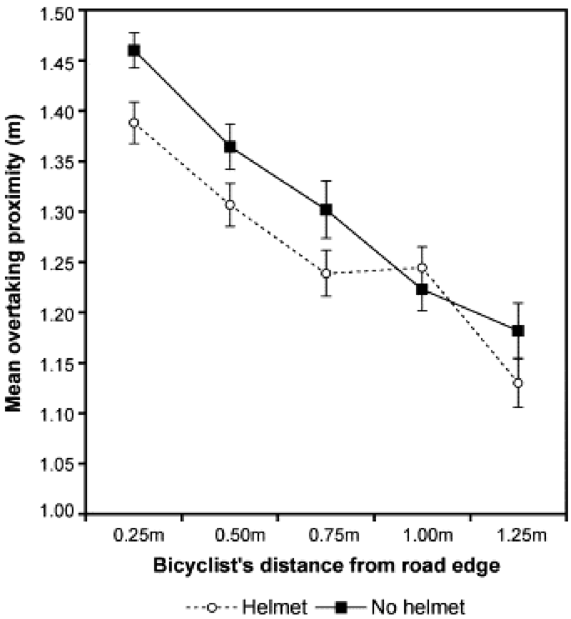


Figure 3: Mean overtaking distances as a function of bicyclist's riding position (Walker, 2007)

Dufour, (2010) reported that the average distance that a cyclist keeps from the curb is 0,25 meters. Dozza et al., (2016) shared a similar result of 0,3 meters.

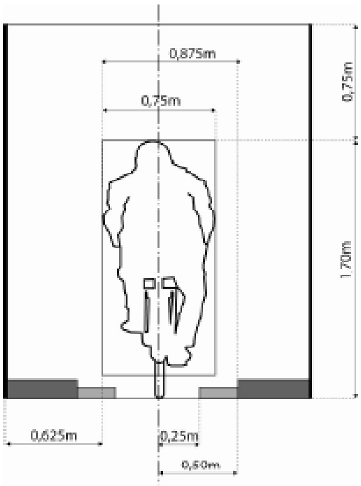


Figure 4: Bicyclist's distance from road curbs. (Dufour, 2010)

2.1.3 Cyclist personal characteristics.

Besides the characteristics of the overtaking maneuver, personal characteristics of the cyclist may influence the distance that drivers keep when overtaking. However, no statistically significant results were found for the dependence of distance of overtaking on the age of a cyclist, the style of cycling or the type of cyclist's clothes (Debnath et al., 2018).

Studies have shown that only the gender of a cyclist affects the distance of overtaking. Drivers of conventional cars prefer to keep more distance from female cyclists than from a male cyclists (Chuang, Hsu, Lai, Doong, & Jeng, 2013; Walker, 2007). Walker (2007) shows that the difference in the average overtaking distances of men and women was more than 14 cm, and this result was statistically significant.

2.1.4 Vehicle characteristics

Motorized vehicles can be buses, trucks, conventional cars, mini-cars. Larger vehicles have a longer passing time, which may affect the cyclist's perception of the subjective risk level. As a result, a cyclist may show less stable riding behaviors. Chuang et al. (2013) found that a longer passing time influence on the observed increase in wheel angle and speed. Even though the influence of a vehicle characteristics on the passing distance is expected, literature studies show controversial results. Walker (2006) reported that bus drivers have lower passing distances than car drivers. In contrast, Chuang et al. (2013) stated that there was no statistical significance in the study of the behavior of bus drivers. The master thesis research assumes that the results of the experiment with the car can still be used in the I-AT project.

2.2 Objective risk level

2.2.1 Surrogate safety measures

Surrogate Measures of Safety (SMoS) are used to assess potential road network conflicts (Morando, Tian, Truong, & Vu, 2018). The SMoS evaluates conflicts appearing during transport interaction in a safe way, therefore it does not require accident studies (Gettman & Head, 2007). Conflict of the two road users is defined by Gettman & Head (2007) as "an observable situation in which two or more road users approach each other in time and space for such an extent that there is risk of collision if their movements remain unchanged.". The SMoS uses the frequency of the lower risk events (conflicts) to predict the high-risk events (crashes) (Mullakkal Babu, Wang, Arem, & Happee, 2017). Some well-known Surrogate Measures of Safety represented in the Table 1.

Table 1: Surrogate Measures of Safety (Gettman & Head, 2007).

Surrogate Measures of Safety	***Unit of measure***	***Description***
Gap Time (GT)	Second	The time interval between the completion of the turning maneuver of the vehicle and the arrival time of the intersecting vehicle, if both vehicles continue to move at the same speed and trajectory.
Encroachment Time (ET)	Second	The time interval during which the turning maneuver of the vehicle block the road for the through vehicle.
Deceleration Rate (DR)	Meters/second^2	The rate at which the vehicle must decelerate to avoid a collision.
Proportion of Stopping Distance (PSD)	Meter	The ratio of the distance available to maneuver of the vehicle to the remaining distance to the predicted collision location.
Post-Encroachment Time (PET)	Second	The time interval between the end of the turning vehicle maneuver and the time when vehicle actually arrives at the predicted collision location.
Time to Collision (TTC)	Second	The predicted time for a collision of two vehicles, if they would continue to move at the current speed and on the same trajectory.

The objective risk was assessed with the Probabilistic Driving Risk Field (PDRF) safety approach. The PDRF is more sophisticated method compared to other Surrogate Measures of Safety (SMoS). This is because the PDRF has severity and probability components, which better reflect different situations (Bhusari, 2018). For instance, some interactions with high severity magnitude do not result in an accident and interactions resulting in accidents do not always have the same magnitude and effects. The PDRF can consider simultaneously the risk of collision with static and kinetic objects, which enhances the reality of risk modeling for interactions with different objects. This approach also allows to combine both lateral and longitudinal dimension risks simultaneously (Farah, Bhusari, Gent, Freddy, & Morsink, 2019).

2.2.2 Probabilistic Driving Risk Field safety algorithm

The PDRF safety measure method was developed by Mullakkal Babu et al. (2017). PDRF can be used to investigate vehicle driving risk appearing in mixed traffic case, when automated vehicle shares the carriageway with other road users. The safety approach models the risk situation as a threat that an object S experiences from object C, designed as a influence field. The field represents a probability and severity of collision between S and C. The crash loss due to a collision is determined by the physical vehicle mass, value of velocity and direction of velocity at the time of an accident. Additionally, the severity of the collision is influenced by the positioning of object C. (Mullakkal Babu et al., 2017). The potential influence of the road objects is modelled as a scalar field – Probabilistic Driving Safety Field (PDSF). This field magnitude is defined by the probabilistic safety field strength. The safety force, used in a field strength, can be based on the vehicle trajectory (offline) or on the automated vehicle onboard sensor prediction algorithm (online).

An automated vehicle can interact both with static and dynamic objects. The PDRF can include Potential field strength and Kinetic field strength. The Potential Field Strength is associated with the threat from the static road objects, such as lane marking, surrounding trees, concrete walls and road signs. The kinetic risk field strength is associated with moving road objects such as bicycles, cars and pedestrians (Mullakkal Babu et al., 2017). The Potential and Kinetic Fields are discussed in more detail in the following sections.

2.2.2.1 Potential field strength

Potential Field Strength is associated with the threat from the static road objects. The Potential Risk can be calculated using the formula below:

$$R_{b,s} = 0.5kM(V_{s,b})^2 \cdot max(e^{\frac{-|r_{s,b}|}{D}}, 0.001)$$

Table 2: Variables of the potential risk field formula

Variables	***Unit of measure***	***Description***
s		A dynamic object experiencing influence from the static object.
b		A static object influencing the dynamic object s.
k	0…1	The parameter of the rigidity of the road boundary object with range from 0 till 1, where k=1 entail that the static object has infinite mass and is not deformed in case of an accident.
M	Kilogram	The mass of the dynamic object s.
$V_{s,b}$	Meter/Second	The velocity of the dynamic object S along $r_{s,b}$
$r_{s,b}$	Meter	The shortest distance between dynamic object s and static object b
$\mathrm{D} = \frac{W}{14}$	Meter	A steepness of descent of the potential risk field, where W is the width of the lane. The collision probability reaches a value of 0.001 in the center of the lane.

As was discussed above, the Potential Risk calculation formula consists of a multiplication between the severity of an accident and the probability of an accident. The crash severity is represented by the term $0.5kM(V_{s,b})^2$. The severity is the magnitude of the crash energy that appears in the event of an accident between objects S and B. Severity is characterized by the value of the rigidity parameter k. The crash probability is defined by the term $e^{\frac{-|r_{s,b}|}{D}}$ which ranges between 0 and 1. The crash probability has an inverse relationship with $r_{s,b}$ and decreases when the distance between interacting objects increases.

2.2.2.2 Kinetic field strength

The Kinetic Risk appears from interaction with dynamic objects. The PDRF considers the inelastic collision process. In the process of inelastic collision, both objects move together after the first contact. Kinetic Risk is represented by the following formula:

$$R_{n,s} = 0.5M_s\beta^2|\Delta V_{s,n}{}^2| \cdot p(n,s)$$

Table 3: Variables of the kinetic risk field formula

Variables	***Unit of measures***	***Description***
S		A dynamic object that is experiencing risk from another dynamic object.
n		A dynamic object that influence on the object S
M_s	Kilogram	A mass of the dynamic object
$\beta = \frac{M_n}{M_s + M_n}$	Kilogram	A mass ratio of the interacting objects
$\Delta V_{s,n} = V_s - V_n$	Meter/Second	The counteracting velocity between objects S and n

Kinetic Risk also consists of a combination of severity and probability of an accident. The $0.5M_s\beta^2|\Delta V_{s,n}{}^2|$ denotes the severity of the Kinetic Risk, which is a magnitude of the crash energy that object S absorbs in case of the accident between objects S and N. The crash energy amount is inversely proportional to the individual mass, therefore an object with a smaller mass will dissipate more energy than a heavier object. The Kinetic risk obtains maximum value when position of objects S and n overlaps.

The PDRF method assumes that risk appears because an object S maintains its motion not knowing the motion of an object n. The second component in the kinetic risk formula is the probability of a collision p(n,s). The probability of collision monitors the trajectory of the object S and predicts the possible future motions of objects n. The collision appears if two objects come at the same place at the same time. Following that, the collision probability is characterized by a spatial overlap. The crash probability changes in a range from 0 to 1.

The collision probability likelihood is related to the probability of the object n acceleration. We know the trajectory of s and predict the trajectory of n. The following steps calculate the collision probability likelihood. The trajectory of n is unknown; therefore acceleration is treated as a random variable. The variability of acceleration is represented as a normal distribution. The parameters of the acceleration distribution are estimated with the following formulas:

$\mu_A = \frac{1}{T}\int_0^T A(t) \cdot dt$ – the mean acceleration

$\sigma_A^2 = \frac{1}{T}\int_0^T [A(t) - \mu_A]^2 dt$ – the standard deviation of the acceleration.

Where T- is the sampling time duration

A(t) -is the acceleration function over time.

The acceleration variability distribution is equal to the relative likelihood of occurrence. The collision likelihood is equal to the probability of the acceleration of object n, calculated with the formula below:

$$A_{x,n} = \frac{\Delta X - \Delta V_x \cdot \tau}{\tau^2} \; ; A_{y,n} = \frac{\Delta Y - \Delta V_y \cdot \tau}{\tau^2}$$

Finally, based on the acceleration of n (that is a random variable) the collision likelihood can be found:

$$p_L(n,s|\tau) \; = \; N(\frac{\Delta X - \Delta V_x \cdot \tau}{0.5 \cdot \tau^2}|\mu_x,\sigma_x) \cdot N(\frac{\Delta Y - \Delta V_y \cdot \tau}{0.5 \cdot \tau^2}|\mu_y,\sigma_y)$$

Where:

N- is probability density function

μ – is the mean of the distribution

σ- is the standard deviation of the distribution

$\Delta X = X_s - X_n$; $\Delta Y = Y_s - Y_n$ – relative spacing in longitudinal and lateral directions

$\Delta V_x = V_{X,s} - V_{X,n}$; $\Delta V_y = V_{Y,s} - V_{Y,n}$ – relative velocity in longitudinal and lateral directions

The reachable state for interacting objects can be represented as quadrilateral polygon. The zone O of potential collision zone is defined using the geometry of two interacting static objects. The overlapping region O also has the shape of a polygon, as shown on the Figure 5. The region O is converted to acceleration domain by the following formula:

$$A_x^c = \frac{(x^c - x_n(0)) - V_{x,n}(0) \cdot \tau}{0.5 \cdot \tau^2}$$

$$A_y^c = \frac{(y^c - y_n(0)) - V_{y,n}(0) \cdot \tau}{0.5 \cdot \tau^2}$$

Where x^c, y^c denotes the corner positions of overlapping region O.

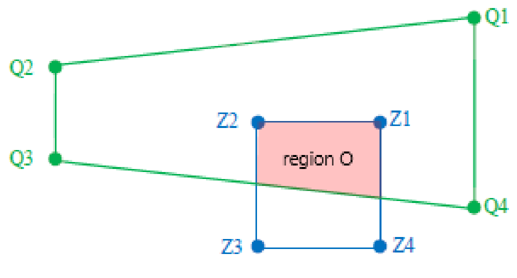


Figure 5: Geometric representation of polygons (Mullakkal Babu et al., 2017).

After the acceleration domain of the overlapping region and the collision likelihood are found, the collision probability can be obtained by integrating the joint acceleration distribution over A0:

$$p(n,s|\tau) = \iint_{A0} (N(A_x|\mu_{x,}\sigma_x) \cdot \; N(A_y|\mu_{y,},\sigma_y) \cdot dA_x \cdot dA_y)$$

2.2.2.3 Total risk strength

The Total Risk combines risks posed by multiple road objects based on the superposition property of fields (Mullakkal Babu et al., 2017). The theory of superposition states that the solution of the complex problem is a sum of the simpler individual problems (Reilly, Franke, & Bennett, 1984). A total risk also comprises from the Potential Risk Strength and a Kinetic Risk Strength. The PDRF represent Risk of interaction as a cut-in risk situation graph. An example of the graph can be seen on Figure 6. The graph has a shape of the wave changing with the time of experiment. The superposition states that the shape of the joint wave is determined by algebraically adding individual waves together (Reilly et al., 1984). In the case of the master thesis research the total risk wave is composed by a Kinetic Risk wave and a Potential Risk wave.

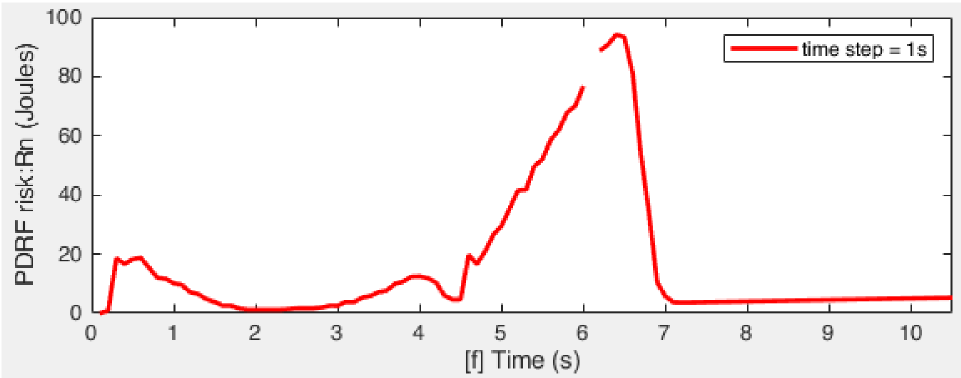


Figure 6: PDRF Total Risk

Road users are not aware of the Objective Risk Level that they experience on the roads. They choose their actions based on the Subjective Risk Level value. In order to maintain a safe interaction between an automated vehicle and other road users, the relationship between automated vehicle actions and the corresponding Subjective Risk Levels should be investigated.

2.3 Subjective risk level and trust

2.3.1 Trust

The process of operation of automated vehicles is uncertain. The interaction between automated vehicles and people always contain a certain risk, as AV and people are interdependent. Thus, trust of the other road users is crucial to the operation of an automated vehicle. An appropriate level of trust is a key to the high safety level and productivity of the human-automated system interactions (Hoff & Bashir, 2015). Trust directly affects the willingness to use an automated system and trust defines the proper use of the system (Ekman, Johansson, & Sochor, 2018). The interaction process is impossible without reliance on the system. Mayer, Davis, & Schoorman D. (1995) define trust as the willingness of one interacting object to be vulnerable to actions performed by another interaction object. The willingness to trust should be consistent with the considered system (Ekman et al., 2018). If systems are used wrongly, an accident may occur. Failures appear if users misuse automation by over-trusting the system, or if users disuse automation system by under-trusting it (Hoff & Bashir, 2015). People rely on automation only if they trust the system, otherwise users will refuse to automate a system they do not trust (Lee & See, 2004). Following that, lack of trust leads to the disuse.

The concept of over-trust to the system can also cause troubles during interaction. Lee & See, (2004) reported that people tend to over-trust novel automated systems. Over-trust can lead to unsafe situations, as people's trust exceeds the capabilities of an automated system. Besides safety reasons, over-trust is undesirable, as it can lead to a rapid disappearing of trust. Using the system in an unplanned way may lead to system errors. Systematically appearing errors will lead to loss of user's confidence. Restoring trust is harder than gaining (Lee & See, 2004).

If end-users do not obtain confidence in an automated system, they can still decide to cooperate with it (Mayer et al., 1995). Lack of trust will also lead to the declining systems benefits and generally ineffective collaboration. It can be concluded that cooperation between an automated vehicle and users is not safe and not productive without trust.

The trust level that we perceive for different objects can be obtained from an analogic or analytical judgements. Analogic judgement is based on a well-known social judgement about an object. Our attitude to the object is determined by a pre-defined societal opinion. If the concept is new for us, we can form trust analytically. We build our judgement about an object by evaluating the subjective trust characteristics observed during the interaction with an object (Hoff & Bashir, 2015). The concept of automated vehicles is new to society. Currently, most users choose the analytical way to build trust. To construct an interaction process that will be perceived as highly trustable, it is necessary to examine the attributes that affect the trust level.

2.3.2 Trust concepts.

As trust is a core concept for the successful interaction between objects, many researches evaluated factors influencing trust formation in different interaction processes. Interaction scenarios may differ with the interacting objects, but all cooperative relationship are characterized by uncertainty (Hoff & Bashir, 2015). Following that, trust concepts can relate to the interaction between road users and the interaction between person and automated system.

Mayer et al. (1995) published one of the most influencing papers on the reasons and outcomes of the organizational trust. They stated that a person's trust depends on human individual propensity and trustworthiness of the interacting object. Human individual propensity stands for the basic level of trust that individual generally experience to other people. Trust worthiness is characterized by the attributes of ability, benevolence and integrity. Ability stands for the level of skills and personal characteristics that an influencing person obtains. These attributes influence authority in a certain area. The trust level will vary based on the level at which a person is able to fulfil a task. Benevolence represents the extent to which trustor believe that the influencing person is interested in the trustor well-being. In case of that attribute, the level of trust is influenced by the level of matches of the two interacting humans' interests and final goals (Hoff & Bashir, 2015). Integrity is the extent to which the trustee follows the principles accepted by the trustor. In the case of the integrity attribute, the level of trust does not depend on the actual actions of the system, but on the match between actions and human values of the system.

Another concept of trust attributes was proposed by Lee & See (2004). Lee et.al (2004). investigated the interaction between human and automated system and concluded that for this specific interaction trust depends on the performance, process and purpose of an automated system. Performance attribute vary trust based on the ability of the system to fulfil human's tasks. Process-based trust connected to the extend at which user can understand the actions of the automated system. Purpose-based trust fluctuated based on the level at which designed system purpose and human system needs correspond to each other (Lee & See, 2004). Körber (2019) merges research from Mayer (1995) on the human-human interaction and research from Lee (2004) on the human-automated system interaction and build a novel human-automation interaction model.

Lee (2004) states three influencing attributes: performance, process and purpose, described in detail by Korber (2019). New attributes are reliability, understandability and intention of developers. From the work from Mayer (1995), Korber (2019) learned that the trust level influence subjective trust characteristics, adding therefore the individual component of propensity to trust. Besides attributes mentioned at works of Mayer (1995) and Lee (2004), Korber (2019) used new characteristics. Korber stated that familiarity influence on the trust to technology. He found out that previous positive (or negative) experience with a similar (to the examined) system influence on the current system's reliability level. A model designed by Korber (2019) to evaluate trust in the automated system presented on Figure 7.

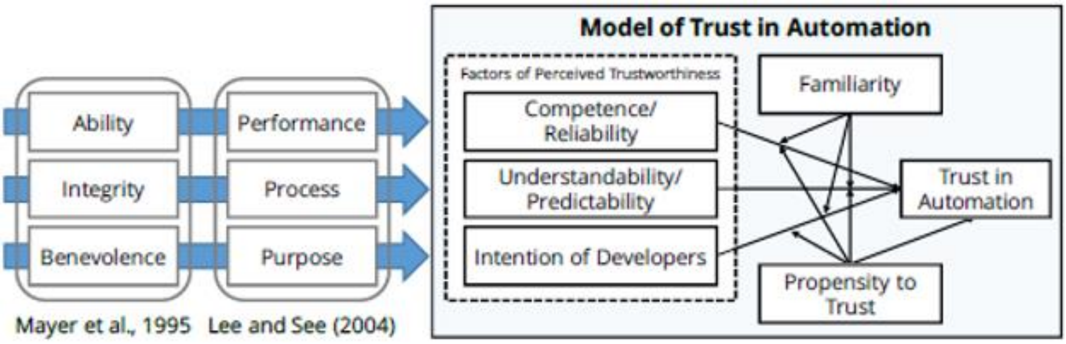


Figure 7: Model of trust in automation (Korber, 2019)

In addition to the general trust in technology, the interaction of an automated vehicle with a cyclist is characterized by several specific attributes. These attributes are directly related to the process of interaction, including the behavior of drivers with an automated vehicle.

2.3.3 Subjective risk attributes of automated vehicle and cyclist interaction.

Automated vehicles interact with various types of other road users. One of the most challenging types of interaction is the one with non-motorized modes. Vulnerable road users have large flexibility in interaction scenarios with automated vehicles. If a pedestrian or cyclist feel in a high risk level, they may decide not to interact with automated vehicle. However, distrust of other road users to AV technologies will have a negative impact on the future of automated vehicles.

Some studies were done in order to investigate factors that influence pedestrian trust in the automated technologies. Researchers reported that on the decision to cross the road in front of automated vehicle the highest influencing factors are speed of the vehicle and distance to the AV (Oxley, Ihsen, Fildes, Charlton, & Day, 2005; Rodríguez Palmeiro et al., 2018; Yannis, Papadimitriou, & Theofilatos, 2013). Other factors influencing on the pedestrian decision to cross in front of an AV were the vehicle deceleration level, familiarity of environment for pedestrian, weather conditions, traffic volume level (Lagstrom & Lundgren, 2015), the size of the automated vehicle and the gender of the pedestrians and whether pedestrian crossing alone or in a group of people (Yannis et al., 2013). The interaction of human road users involves an implicit communication channel. The direction of sight and the overall facial expression of the driver may give the pedestrian sufficient information input. Rodríguez Palmeiro et al. (2018) found that the decision to not cross in front of AV was influenced by the driver inattentiveness. Lagstrom & Lundgren (2015) reported that if pedestrians feel unsafe when interacting with an automated vehicle, people tend to choose to wait until AV performs a complete breaking operation.

2.4 Conclusion

This chapter gives an overview of the literature relevant for this research. The research works with the interaction scenarios when automated vehicle approaches cyclist from behind. One of these scenarios is overtaking. The chapter describes four stages of the overtaking maneuver and listed attributes relevant for the safety of interaction. Research mentioned that for the overtaking vehicle speed of 40km/h the overtaking distance is 1,5m, while for higher speed of 60km/h-80km/h the distance becomes 2m. Another attribute is the cyclist distance to the curb, found equal to 0,25-0,3 meters. For the overtakings vehicle characteristics are also relevant, such as the size of the vehicle, as longer passing time influences the speed of cyclist. Attributes found in the literature will be used for the scenario design.

The risk level is assessed with the objective risk and subjective risk. The chapter gives an overview of the surrogate measures of safety and presents the Probabilistic Driving Risk Field safety method applied in this research to assess the objective risk. The chapter explained the benefits and principles of this method according to the literature.

The literature on the ways of assessing the subjective risk was shown. Previous studies show the importance of the trust concept for the safety of the interaction, as undertrust and overtrust violate the understanding of cyclist of the automated vehicle capabilities. In this chapter was introduced a Korber trust assess model which is used in this research to evaluate trust.

Next, attributes influencing on the subjective risk of automated vehicle and cyclist interaction were presented. The most influencing factors are speed of the vehicle and distance to the vehicle. Another relevant factors for the research interaction attributes are: weather conditions, the size of the automated vehicle, gender of the participants and attentiveness of drivers.

3 Research methodology

This chapter discusses the methodology of data collection and analysis.

3.1 Data collection method

3.1.1 Field experiment

The experiment method consists of two parts – the pilot experiment and the main experiment. The pilot experiment is the first trial of the experimental scenarios. Results of the pilot experiment provide improvements for the design of the main experiment. This section discusses the overall design of experiment scenarios. The exact changes applied after the pilot experiment can be found in the chapter on the pilot experiment.

3.1.1.1 Participants

In total, 29 people took part in two experiments. The pilot experiment includes 4 participants and the main experiment includes 25 participants. 15 male and 14 female participants from the same age group (mean=25,4; std.=1,3). Participants were recruited by personal invitations on social media.

3.1.1.2 Scenarios

As part of the I-AT project, this research selected AV-cyclist interaction scenarios from the Vaals-Aachen route. Photos of the interactions on the route can be seen on the Figure 8. Two interaction scenarios were identified. The first interaction scenario includes a separate bicycle lane. This scenario was not included in the research, as in this case the automated shuttle bus will not interact much with cyclists. The second interaction scenario includes a shared carriageway. In this case, the ASB have to follow cyclist and, if possible, overtake. This scenario became the basis of the master thesis scenarios.

Figure 8: Vaals-Aachen route, examples of interactions between ASB and cyclists

The interaction process is also influenced by the interaction parameters. The Vaals-Aachen route was further studied to determine which infrastructure attributes vary for the selected interaction. It was found out that the interaction of the ASB and the cyclist can happened with different right hand side objects: on some streets there was only a curb, on others streets appear parked cars. The right hand side objects were included in the experiment as an attribute. For the safety reasons in the field-experiment, parked cars were replaced with a safe barrier.

In addition to the attribute identified by route analysis, the scenarios include attributes found in literature studies. Literature studies have found that the vehicle overtaking speed and overtaking distance also affect the risk level of interaction. Both parameters were included in the experiment scenarios as independent variables. Literature shows that at a speed of 40 km/h, drivers of conventional vehicles keep a distance of 1,5 m overtaking, or in another words a distance of 2 m from the curb. These findings were taken as the first attribute value.

An important parameter for the following maneuver is the following distance. In the literature, it is assumed that the longitudinal clearance between the vehicle and another moving object should be equal to the stopping distance of the vehicle. The stopping distance of the vehicle used in the experiment is 3 meters at a speed of 12 km/h (Henderson, n.d.). A distance of 3 meters was chosen as a value of the following distance attribute. To establish equal conditions for following and overtaking maneuvers, the overtaking distance attribute will have a second value of 3 meters. In total, the experiment has 4 within-subject variables (2 levels each). All experiment attributes are shown in the Table 4. Each participant experiences all attributes but combined randomly.

Table 4: Experiment variables

Dependent Variables	
Distance from cyclist to the right-hand side objects.	
Subjective risk level	
Objective risk level	
Cyclist trust in AV technologies	
Within-subject variables (independent)	***Categories***
AV Overtaking Speed	Cyclist speed + 5km/h Cyclist speed + 10km/h
AV Overtaking Distance	1,5 m 3,5 m
Right-hand Side Condition	Curb with Asphalt Path Curb with Green Grass

Each scenario includes the following maneuver, when the vehicle follows the bicycle, and the overtaking maneuver, when the vehicle overtakes the cyclist. The Figure 9 shows an example of one experiment scenario. Each scenario includes all attributes; however, attributes are not repeated between maneuvers. All participants experience all attributes. However, in order to study the correlation between risk level and learning, attributes are selected for different participants in a random order.

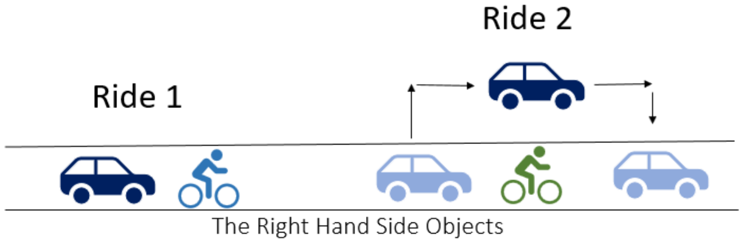


Figure 9: Experiment scenario example.

The experiment vehicle only operates in manual mode. However, the Introduction paper informs the participants that the vehicle can be operated both in manual mode and in automated mode.

Following that, the experiment can capture the behavior of participants in interaction with an automated vehicle and in interaction with a conventional vehicle.

3.1.1.3 Experiment location

The safety of the riders must be guaranteed. Following that, the experiment was conducted on a quiet and low-hierarchy street. The road consists of two lanes for driving cars and two lanes for bicycles. The route of the experiment route was direct, without turns, and the complete street was closed for traffic. Initially, there was no right-hand side blocking on the Hertjeslaan street. For the pilot-experiment, a barricade from wooden pegs and white-red ribbon was built to block the right-hand side of the cyclist. The picture of barricade can be seen on Figure 10. The height of the barricade was 1,5 m, which corresponds to the eye level of the cyclist (City of Toronto, 2017).

Figure 10: Right hand-side barrier

3.1.1.4 Experiment bicycle

An equipped bicycle was used to collect objective data. The bicycle was equipped at the Transport and Planning Laboratory by Peter van Oossanen, Edwin Scharp and Paul van Gent. The bicycle was equipped with a lidar, a camera and GPS, accelerometer sensors. The positioning of the sensors can be seen in the Figure 11.

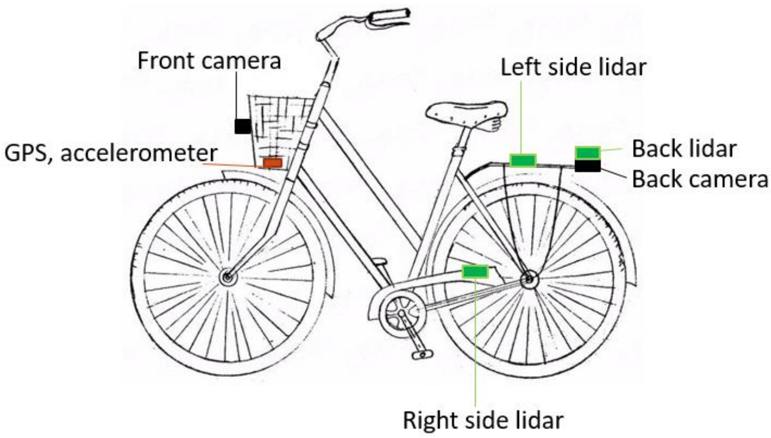


Figure 11: Sensors placement at bicycle

Lidar is an abbreviation for the Light Detection and Ranging. Lidar obtains information from an optical laser signal. The transmitter emits a signal that is reflected by a target and detected by a receiver. Lidar has a short-wave length, therefore detecting small object. Different types of Lidars can obtain information about the range, chemical properties and velocity of the object (Rock & Park, 2007). In this research, the bicycle is equipped with three Lidars. Lidars capture the distance from the bicycle to the vehicle, during following and overtaking maneuvers, and the distance from the bicycle to the curb.

The Global Positioning System (GPS) provides information about position and velocity of the object and the collection time. In this experiment, both the vehicle and the bicycle are equipped with a GPS sensor.

To collect a sufficient number of measurements in an overtaking maneuver, Lidar and GPS sensors collect 5 measurements in 1 second. When the experiment ends, the measurements taken by the sensors should be divided into trips. As the sensors capture data constantly, and not just during the actual rides of cyclists.

3.1.1.5 Data processing

Three types of analysis were used to separate all of the inputs into cycling rides: time of cycling, speed of cyclist and geo-fences. The combination of three types of analysis allows to minimize the error in determining the trip. Time of cycling method corresponding to the data captured during the experiment. During the experiment, organizers determine the start and end time of each trip of the participant. Additionally, video files recorded by the bicycle camera indicate the time of recordings. Combining video files and start and end times, the exact time of each trip was determined. Speed of cyclist method captures cycling speed with input data from the IMU part of the Lidar sensor. When the speed of cycling is higher than zero, we can assume that cyclists are in motion. Geo-fence method is the most accurate method of the three analyzes. Geo-fence is a virtual representation of a real geographic area built with GPS-coordinates. In this research, geo-fencing shows when a cyclist enters an area of interest, as shown in the Figure 12. The geo-fence consists of 2 small square sites where participants fill out a questionnaire and one big middle section where participants experience interaction with a vehicle. Smaller sections help track if a participant changes location on one side of the road to the other side of the road.

Figure 12: Geo-fence.

3.1.1.6 Accuracy of measures.

Sensors used to collect the data were tested for accuracy. The first approach for accuracy verification was to compare manually measured distances to objects, latitude and longitude during the experiment with sensor measures. The second approach was applied in data analysis phase, comparing pre-designed parameters such as width of the bicycle lane, following and overtaking distances to the Lidar measurements.

The Lidar's measurements accuracy can be judged depending on the distances measured by the sensor. During the experiment, participants rode a bicycle along a 1,5 m wide bicycle path. It is expected that Lidar will show the distance to the Right Hand Side (RHS) within the border of 1,5 m.

Assessment of the level of Subjective Risk includes an assessment of Trust. Trust can be evaluated using neuroscientific methods, behavior measures and questionnaires (Körber, 2019). Trust is not directly observable, which means that people can still cooperate with an automated system even without trusting it (Körber, 2019; Mayer et al., 1995). People who trust the system and people who do not trust the system can behave similarly. Data from sensors that collect skin response and heart rate cannot give useful insights on trust. As the level of risk in the field experiment is similar to daily stress (Rodriguez Palmeiro et al., 2017), only self-reported facts can reflect the real levels of trust and risk. Therefore, this research will apply questionnaires as a means to evaluate confidence of participants in response to automated vehicles.

3.1.2 Questionnaire.

Four questionnaires were designed for different research phases. They cover personal characteristics of the participants, basic trust in technologies, familiarity with vehicle automation and level of experienced risk.

Hoff & Bashir (2015) define four main personal characteristics influencing the disposition trust in automated technologies: culture, age, gender and personality. The questionnaires include a personal characteristic part with a question about gender. Besides personal characteristics included in the questionnaire, the level of sensation seeking may be relevant to the research. However, sensation seeking test was not included in the questionnaire to ensure high concentration from the respondents.

Trust in technology was assessed using a questionnaire developed by Körber (2019). The questionnaire uses a multiple-item scale, which measures the attitude of the respondent to more than one attribute of an object. A multiple-item scale increases the probability of capturing correct responses, increasing the validity of responses. The use of several elements also reduces the probability of getting measurement error (Körber, 2019). In this research, the multiple-user scale is applied as a Likert-scale. This is a ranking scale in which respondents indicate their agreement with the questionnaire statements. The Likert-scale applied in this research ranges from 1 to 5, meaning “strongly disagree” and “strongly agree” respectively. The 5-point scale was adopted because it represents an adequate level of detail. Increasing the number of points on the scale can lead to situations in which participants cannot perform self-analysis with satisfactory accuracy.

The Körber (2019) questionnaire on trust to technologies has 6 parameters: reliability; predictability; familiarity; intention of developers; propensity to trust and trust in automation. The author designed 19 questions including inversely formulated questions. Reverse questions reduce the bias of the answers, as it is expected that someone who is positive about the questionnaire topic concept should not agree with the inverse statement. Therefore, they help to check the concentration of the respondent.

In this research, subjective and objective risk levels are evaluated. The perceived risk level is captured by a risk scale of 100 degrees. Initially, a scale with a step of 10 degrees was used, but a pilot-experiment shows that it's better to use a scale with a step of 5 degrees.

3.2 Data analysis methods

3.2.1 Probabilistic Driving Risk Field

The Probabilistic Driving Risk Field (PDDRF) method calculates the risks of interaction between an automated shuttle bus and cyclists. The PDRF requires a lot of input data. Some of the required data are given in the vehicle technical specification and literature studies on cyclists, for example the parameter of rigidity of the road boundary object. Different right-hand side objects have different parameter of the rigidity of the road boundary object. If right-hand side object does not deform in case of accident the parameter equals to 1. Mullakkal Babu et al. (2017) uses a value of the k equal to 0,61 for the right lane boundary. On the experiment location, there are curbs on both sides. However, on one side of the road there is a pedestrian path covered with asphalt, and on the other side there is grass. A coefficient of 0,61 is used for the pedestrian path and a coefficient of 0,55 is used for the green grass side. A sensitivity analysis shows that a Static Risk with k=0,61 has a risk value of 10% more than a Static Risk with k=0,55.

The master thesis experiment provides most of the data required to calculate the PDRF. The data that needs to be collected can be seen in the Figure 13. The Potential Field needs the lateral distance of the cyclist from the right hand side objects. The Kinetic Risk Field uses longitudinal and lateral position and velocity for both the cyclist and the vehicle. In the master thesis research, the PDRF considers a cyclist as an object of risk taking (object s) and the vehicle as an object of influence (object n). As in the interaction between the cyclist and the vehicle, the more vulnerable user is the cyclist, and in case of an accident the cyclist will be more harmed.

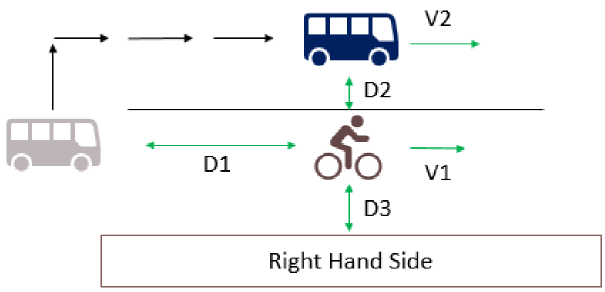


Figure 13: Variables collected from experiment

3.2.2 Statistical analysis

Statistical analysis proves the significance of the observed results and verifies the existence of interactions between variables. SPSS is applied to conduct statistical tests. The statistical analysis in this research was based on the steps defined by Garth (2008) for confirming statistical significance. First of all, a descriptive analysis is performed with the input data, possibly using boxplot graphs in SPSS or other graphs in Excel. A preliminary analysis shows a possible trend in data interaction, which should be considered in detail at the next stage of analysis. To select the correct method for analyzing the interaction between variables, the type of input data should be determined. The analysis methods vary depending whether the data is parametric or non-parametric. Parametricity depends on the type of data: nominal, ordinal, interval or ratio or can be evaluated by checking for a normal distribution.

Any existing data can be divided into the following 4 formats, presented in the Table 5 (Garth, 2008). In addition to the exact data format, the input data can be either parametric or non-parametric. Parametric data is data that is a normally distributed. In this type of data, most of the values are close to the mean value, and other data are gradually decreasing, symmetrically (Garth, 2008). Non parametric data is not normally distributed data. Small samples are assumed to be non-parametric (Jawlik, 2016).

Table 5: Data formats.

Data Format	***Definition***	***Example***
Nominal (Categorical)	The data categorize some attributes. It may be coded as numbers. Numbers is a label, they do not have real meaning.	Gender (male/female) Right hand side object
Ordinal	These data have an order. But order does not have numerical meaning.	Likert scale (1=strongly disagree, 2=disagree, 3=agree, 4=strongly agree) Scenario number
Interval	This type of data is numerical. The distanced between values are meaningful. However, zero value does not have real meaning.	Risk Level Speed
Ration	This type of data is numerical. Both: distanced between values and zero value have meaning.	Following Distance.

Table 6: Parametric and non-parametric data (Bhusari, 2018).

	Parametric	***Non-parametric***
Assumed distribution	Normal	No assumption
Typical data	Ratio or Interval	Ordinal or Nominal
Assumed variance	Homogeneous	No assumption
Observation	Independent	Any

To check whether the input data is parametric or non-parametric, we can conduct a normality check. The Normal Distribution has a bell-shaped, symmetrical on the left and right sides and has tails that never touch the horizontal axis but come very close to it. Normal Distribution can be determined using the following methods: Shapiro-Wilk test, histogram, q-q plot and box-plot.

The last possible separation of input data is separation by collection method. Data can be repeated and independent. Repeated measures are a type of measures when data is collected from the same group of people but under different experimental conditions. Repeated measurements are consistent with the within-subject design (Papadimitriou, 2018). Independent measurement appears when experimental data are collected from different groups of people.

Independent measures correspond to the within-subject design (Papadimitriou, 2018). When a data type is defined for each of the groups mentioned above, a basic analysis can be selected.

The choice of the right analysis method dependent on the purpose of the analysis and the data type. represents the type of data that each analysis method can include. Correlation tests show the influence of variables on each other. There are no dependent variables in this type of analysis. The Chi-Square test analyzes the interactions between categorical variables. The independent/dependent measures test checks the effect of an independent variable on a dependent variable. There are a number of methods in each test category. The method for analysis is selected based on the parametricity of the data and the dependency of measures. Table 8 shows some of the existing analysis methods.

Table 7: Type of variables used in analyzes methods (Delorme, n.d.; Field Andy, 2013; Garth, 2008; Jawlik, 2016).

	Dependent variable	***Independent variable***
Correlation test* *No dependent variables	Linear	Linear
Independent/dependent measures test	Linear	Categorial
Chi-square	Categorial	Categorial

Table 8: Parametric and non-parametric analysis methods (Bhusari, 2018).

	Parametric	***Non-parametric***
Usual central measure	Mean	Median/Mode
Correlation test	Pearson	Spearman
Relation between categorical variables	Chi-square test	
Independent measures, 2 groups	Independent measures t-test	Mean-Whitney test
Independent measures, >2 groups	One way ANOVA	Kruskal-Wallis H test
Dependent measures, 2 measures	Dependent measures t-test	Wilcoxon signed rank test, McNemar test
Dependent measures, >2 measures	Repeated measures ANOVA	Friedman test, Cochran Q
One categorical independent measure and >2 dependent measures	One-way MANOVA	

3.2.3 Generalized Linear Mixed Model

Linear Mixed Model is a linear regression model that contains hierarchical design. In hierarchical design, the data is repeatedly collected from the same individual. When that occurs, answers from the same participant are correlated (West, 2009). The Linear Mixed model expresses the relationship of the target variable from the independent variables and works with the parametric target variable. The Generalized Linear Mixed Model (GLMM) works with the non-parametric distributed dependent variable (Dickey, 2010).

Independent variables can be described by the effect groups (Winter, n.d.). LMM includes fixed and random effect groups. The fixed effects stand for the parameters that are constant for the participant, as fixed parameters include all possible levels of parameter in the study design. For example, gender is a fixed effect, since we know all levels of this parameter – female and male, and this value will not change for participant. Random factors include parameters which may have variations per participants. They represent randomly sampled values from the larger population of levels (Starkweather, 2005; West, 2009). Random parameters have by-subject and by-item variation. By-subject variation is originated from the participants basic features of character and by-item variation accounts for the differences in the conditions of each levels of each independent variable (Winter, n.d.). To account for variation per participant the MLM assumes random intercepts for each participant.

Different combinations of fixed and random effects can have different influences on the model fit. The predicted values plot and an information criterion gives information on the model fit. Lower Akaike Corrected and Bayesian criterion values mean a better the model fit. The perfect model fit corresponds to the values of 0, while the perfect fit in the graph has to be represented by points following the 45 degree-line pattern (IBM SPSS 23.0.0, 2014). Besides model fit, the statistical significance of including parameter as a random effect can be checked with the p values of each of the included random effects. The model outcome does not directly include the p-value for the random effect, therefore the Wald test has to be conducted to check the significance of the parameters. The Wald test calculates the z-value by the ratio between estimated parameters and the standard error of estimated parameters. The z-value can be recomputed to the p-value (IBM SPSS 23.0.0, 2014). The statistical significance of a random parameter indicates that the parameter slope varies for different participants, which means that the regression line in that case vary from the mean assumed regression line (Seltman, n.d.; West, 2009).

The equation of the Mixed Linear Model can be written as follows (Scharfenberger, 2013):

$$S = (\beta_0 \pm a_i) + \beta X_{ij} \pm b_j$$

Table 9: Variables of the regression equation of the GLMM

Variables	***Description***
i	Subject
j	Plot
S	Dependent Variable Value
β_0	The intercept estimates mean value
a_i	The variability between participants
β	Fixed effects slope (rate of change), representing the difference to go down (or up) on the slope from one value of parameter to another (Winter, n.d.)
X_{ij}	Matrix of fixed effects
b_j	Variability within one participant

3.3 Conclusion

The chapter discusses the methodology of data collection and analysis. Field experiment was conducted to collect data, consisting from 2 parts: pilot-experiment, used to test the experiment scenarios and overall organization of experiment, and main experiment. Experiments include 30 participants, with an equal number of male and female cyclists. All participants are from the same age group ($mean = 25{,}23;\ std. = 1{,}3$)

Interaction scenarios include the following maneuver, when the vehicle follows the bicycle, and the overtaking maneuver, when the vehicle overtakes the cyclist. Both following and overtaking are tested in automated and in manual modes. Additionally, a combination of parameters is applied for each interaction. The research includes 3 interaction attributes: vehicle overtaking distance, with 1,5 m and 3,5m; vehicle overtaking speed, with plus 5km/h and plus 10km/h, and right hand side object, with green grass and with an asphalt path. For the right hand side object in the pilot-experiment, a white-red stripe barricade was built on the side of the green grass, which represents a scenario with parked cars.

The experiment includes equipped bicycle and equipped car, with following sensors: GPS and accelerometer, cameras and lidars. The data was processed with the geo-fencing technique and later the accuracy of the input data was checked by comparing sensor detections and measurements taken during the experiment.

For the subjective risk data collection, questionnaires were used. They cover personal characteristics of the participants, basic trust in technologies, familiarity with vehicle automation and level of experienced risk. The self-reported perceived risk level is captured by a risk scale of 100 degrees. The trust was assessed with a 5-point likert scale and 6 sections: reliability; predictability; familiarity; intention of developers; propensity to trust and trust in automation.

For the objective risk analysis, the Probabilistic driving risk field was applied. The PDRF includes multiple input parameters. For the static field, the parameter of rigidity of the road boundary object is specified. A coefficient of 0,61 is used for the pedestrian path and a coefficient of 0,55 is used for the green grass side.

The dependency of the subjective, objective risks and trust from the attributes was assessed with statistical methods. The statistical analysis includes initial tests, this chapter discusses how to choose the right test for analysis. For the regression assessment the generalized linear mixed model was selected. The chapter discusses how to apply the model and the reasons why the GLMM was chosen.

4 Pilot experiment

The core of the methodology of the research is a field experiment. Before the main field experiment, a pilot-experiment was conducted. The pilot-experiment evaluates the feasibility of the approach and illuminates weaknesses in the organization of the experiment, data collection methods and data analysis methods. Additionally, the pilot test results help to select the most promising test scenarios for the main experiment.

4.1 Experiment organization.

The pilot-experiment took 1 day and involved 4 participants, two male and two female cyclists. One participant took 1 hour to complete the experiment. One cyclist participated in 4 designed experiments. Each scenario includes 1 ride during which the participant experienced both following maneuver and overtaking maneuver. The vehicle follows the participant in the first 15 seconds and then overtake. The overtaking distance was 1,5 meters. The following distance was 5 meters.

In all interaction scenarios, the vehicle operated in manual mode. The aim of the master thesis research is to identify differences in the behavior of a cyclist when interacting with a conventional vehicle and when interacting with an automated vehicle. The document "introduction to the experiment" mentions that the vehicle can be operated in automated and manual modes. The moment when the vehicle was operated in automated or manual mode was not pre-specified for the participants. After each interaction scenario, participants mentioned how they perceived the interaction mode in this part of the route.

4.2 Pilot experiment results

To make the selection of attributes for the final experiment, the data of the pilot-experiment were analyzed with preliminary descriptive analysis.

4.2.1 Trust attributes of the interaction between a vehicle and a cyclist.

During the experiment, participants were asked in the questionnaire to indicate which attributes of interaction affect the perceived risk level experienced by them. In the section with the question without answer options, participants mentioned distance to the vehicle, overtaking speed of the vehicle and noise of the vehicle. The attributes "distance to the vehicle" and "overtaking speed of the vehicle" were also previously selected by the researcher as influencing factors. The attribute "noise of the vehicle" was not previously mentioned in the literature. The vehicle used in the experiment can be operated both on electricity and gasoline. The car system automatically switches between modes when there is not enough electricity and when speed is increased, the vehicle switches to gasoline power and the vehicle changes its noise.

4.2.2 Trust Level

During the experiment, each participant experienced 5 rides (Figure 14). The Trust Level increases after the first ride and then remains stable. In the last ride, trust level scatter of data shows a higher value. An increase in scatter value indicates that the trust level of some participants increases also in the last ride. The increase of the trust level can be result of the familiarization of participants with the automated vehicle.

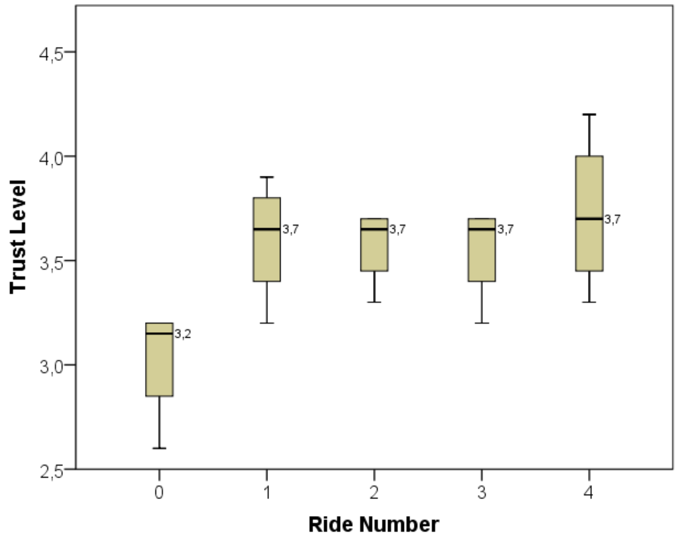


Figure 14: Dependence of the Trust Level from the Ride Number.

The statistical analysis shows that the trust level of the participants does not depend on the right hand side object and overtaking speed. Also, it was not important whether the experiment began at a higher or lower speed or whether the right hand side was blocked or free. The only attribute that affects trust level is gender. Male participants generally had a higher trust level than female participants.

4.2.3 Subjective risk level

The Subjective Risk during the Following maneuver is presented in the Figure 15**.** The 0 ride represents a cyclist riding on the route without the vehicle. The risk level increases when participants meet the vehicle for the first time and remain unchanged in all further rides. However, in the first ride the scatter is higher, and the population median is higher. This may indicate that at the beginning of the experiment participants experienced a higher perceived risk level. The Subjective Risk Level during the Following maneuver does not depend on the attributes of the experiment. In the same way, trust to Following Maneuver has not changed depending on the Gender and RHS objects. Some participants mentioned that they did not consider following as a separate maneuver. Participants considered following as the first stage of the overtaking maneuver, when the vehicle accelerated for overtaking. Furthermore, the following maneuver had a greater following longitudinal distance than lateral distance of the overtaking maneuver.

Based on these findings, the basic design of the main experiment was changed to ensure equal conditions for maneuvers.

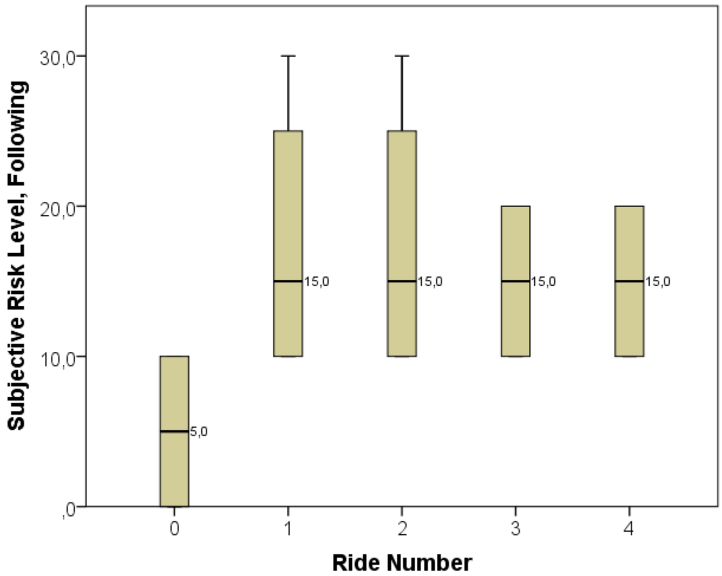


Figure 15: Dependence of the Subjective Risk Level, when Following, on the Ride Number.

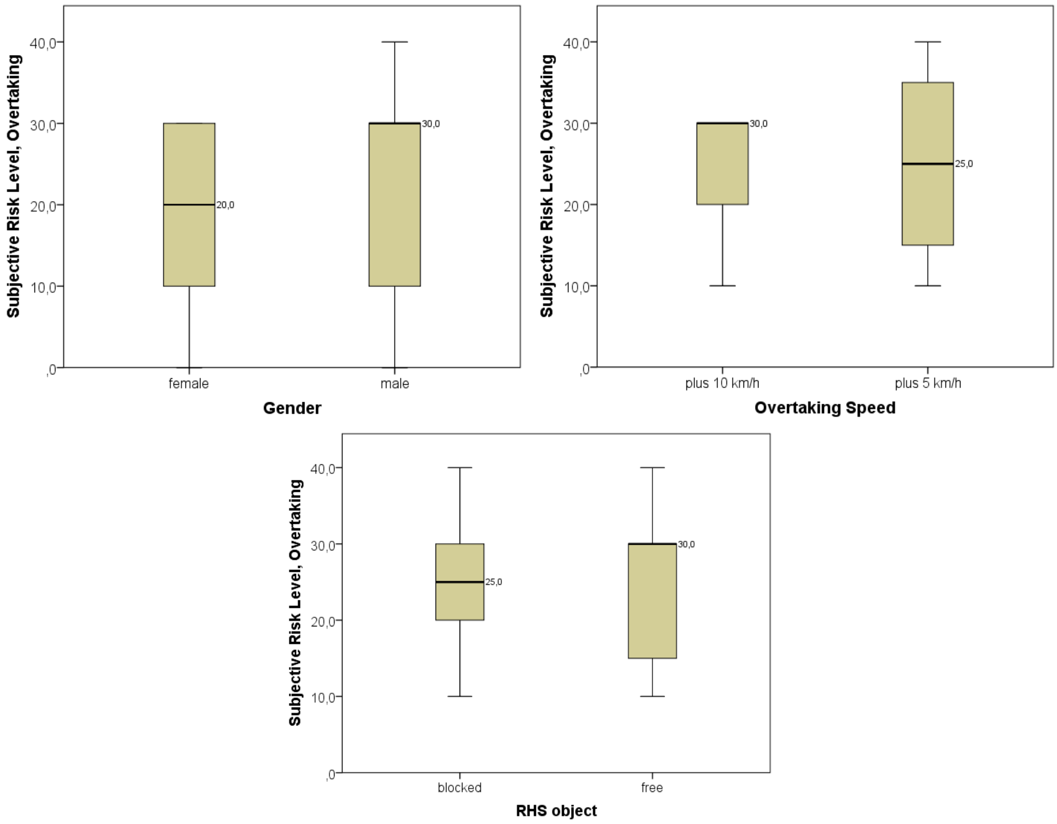


Figure 16: Dependence of the Subjective Risk Level, when Overtaking, on the Gender of Participants; Overtaking Speed; RHS Objects.

The **subjective risk level during the overtaking maneuver (**Figure 16**)** is steadily increasing before the last ride. The subjective risk level shows a dependence on all attributes of the experiment. Male participants experienced a higher perceived risk level that female participants. The overtaking Speed of +10 km/h looked more risky for the participants than the overtaking speed of +5 km/h. The free right hand side (RHS) part, represented by an asphalt curb, was seen as more dangerous than blocked by a red and white stripe RHS. Participants mentioned that a sense of blockage does not affect their risk level. However, the material of the blocking part mattered: the curb is made of strong not-forgiving asphalt, and the red-white strip is safe and does not harm the cyclist. The prototype of the blocked side was a parked car. Parked cars are made of strong material and are dangerous for cyclist. The pilot-experiment shows that the red-white strip does not simulate parked cars. In the main experiment, the RHS attribute should be adjusted or removed.

The master thesis is aiming to answer whether the overtaking maneuver can be as safe for the cyclist as the following maneuver. The pilot-experiment shows that **the subjective risk when overtaking was higher than the subjective risk when following**. However, the pilot-experiment shows that not all participants perceive following maneuver as an independent maneuver. A preliminary analysis shows a negative correlation between **the trust level and subjective risk level (**Figure 17**)**.

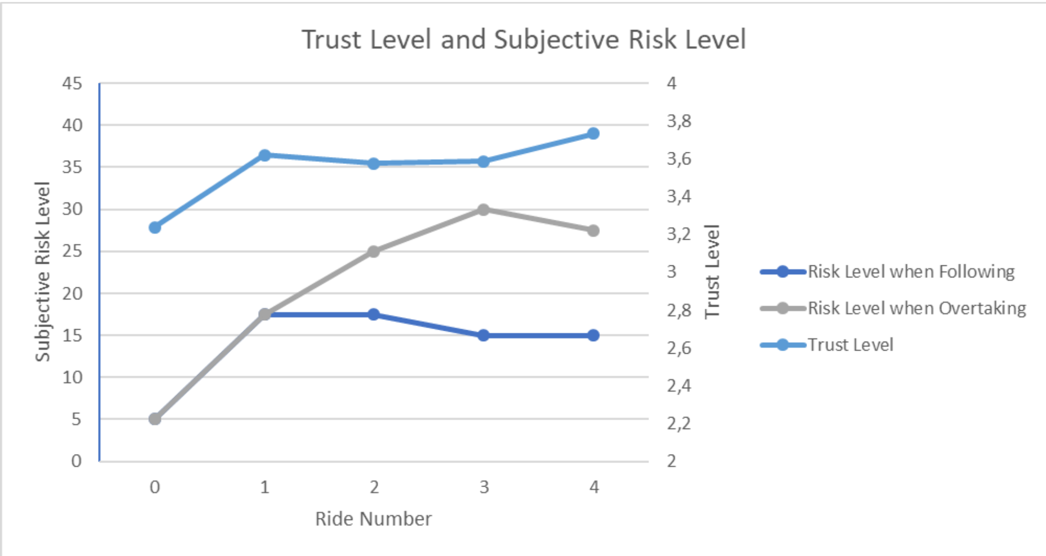


Figure 17: Correlation between the Subjective Risk Level and the Trust Level.

The master thesis research is also aiming to track the attitudes of participants to the automated and conventional vehicles. A pilot-experiment shows (Figure 18) that **the subjective risk level** both in the following and in overtaking maneuvers depends on the **vehicle operating mode**. When the vehicle was in the automated mode, participants reported a higher perceived risk level.

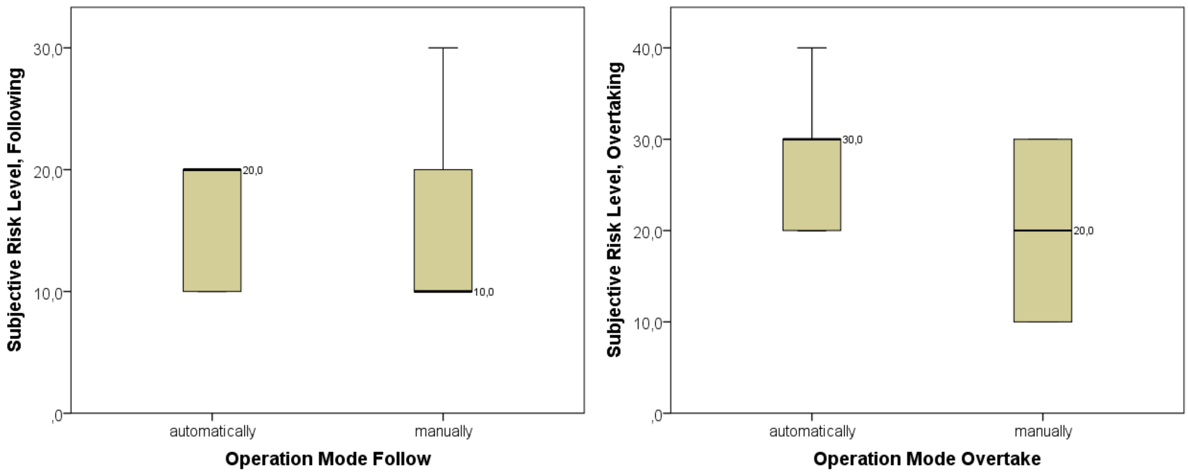
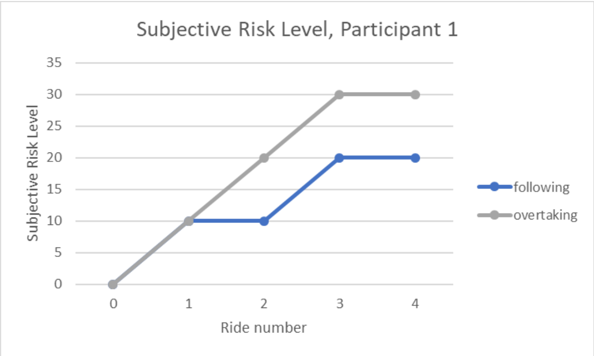


Figure 18: Dependence of the Subjective Risk on the Operation Mode of the Vehicle.

4.2.4 Recommended changes for the main experiment

4.2.4.1 Scenarios.

An individual analysis of the participants shows that the first participant has a stable growth in risk levels throughout the entire experiment while other participants have a risk increase at first followed by risk level decrease in their last ride (Figure 19). This is caused by the learning of vehicle drivers. During the experiment with the first participant, drivers were more careful. In the main experiment, additional time will be left for the pre-training of drivers.



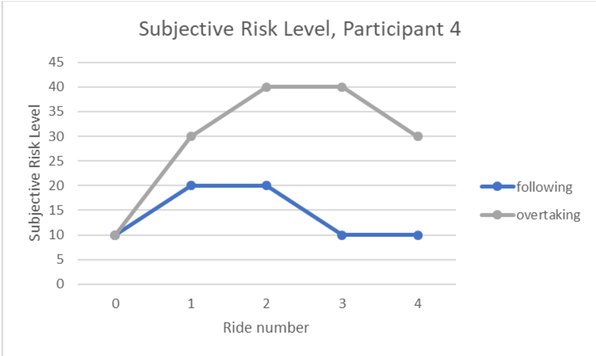


Figure 19: Dependence of the Subjective Risk Level on the Ride Number.

The combination of experiment scenarios for one participant includes designing different combinations between attributes and assigning different attributes first. The Pilot-experiment does not show a relationship between the use of the attribute first and the level of risk reported by the participants. Furthermore, the Pilot-experiment does not show the effect of combinations of attributes on the perceived risk. All combinations between speed and RHS objects shows the same subjective risk level during an overtaking maneuver (Figure 20). The main experiment will not pay attention to combining different right-hand side and different overtaking speeds. Also, no scenarios will be scheduled when the experiment starts with a different RHS.

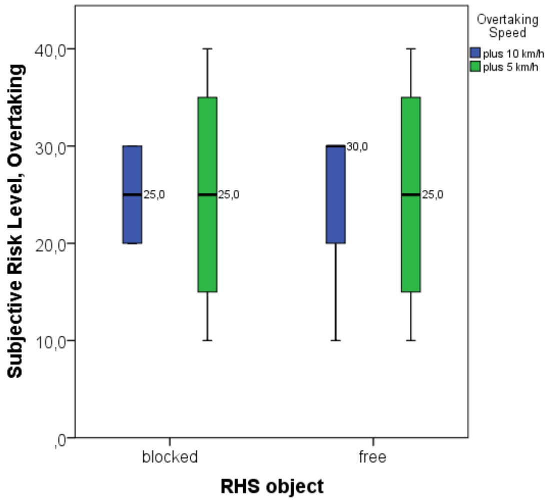


Figure 20: Dependence of the Subjective Risk Level, when Overtaking, on the RHS objects.

The experiment developed the RHS attribute, taking as a prototype of the blocked RHS – parked cars. The pilot-experiment shows that the red-white strip is not considered by the participants as a real danger. The main experiment will not use any blocks in the RHS.

4.2.4.2 Questionnaire.

The Trust questionnaire shows that respondents spend more time on the last questionnaire (13 min), less time on the first questionnaire (11 min) and the least time on the middle questioners (8 min). All participants demonstrate a mean level of trust, or in other words no undertrust or overtrust was found. All participants answered the reverse questions accordingly, showing attention to the questionnaire. However, participants mentioned that questionnaire was too long.

The questionnaire responses show that the participants did not change their attitude to the section “intentions of the developers”(Figure 21). Following that, it was decided to exclude the section “intentions of developers” from the questionnaires. To reduce the time needed to fill out the questionnaire, sections “propensity to trust” and “reliability” were combined and the number of questions was reduced.

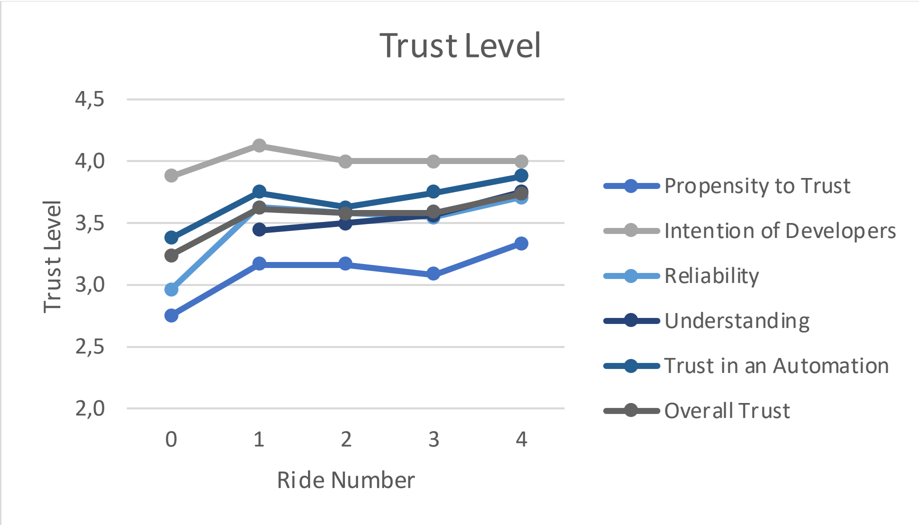


Figure 21: Dependence of the Trust Level on the Ride Number.

The risk scale seems redundant. Respondents did not select risk values above 40% on the risk scale. The 100 % scale exceeded the maximum marked risk level but did not provide sufficient accuracy for low risk levels. Many respondents chose the value of 20%, when it can be assumed that they would like to choose 25% or 15%. For the main experiment, the scale can be modified to have values in step of 5%. Also, all participants choose that they trust conventional vehicle more than an automated one. It was impossible to verify how self-reported trust affects the subjective risk level. Since the questionnaire on trust in technology shows sufficient results, the main experiment will not include question about self-report trust in automated vehicle technology.

4.2.4.3 Vehicle driving mode

After each completed scenario, the questionnaire asks the participant to guess which mode the vehicle was operated during the experiment. Participants mostly choose the same operating mode for both vehicle maneuvers in the same scenario. When participants choose the automated mode of operation, they demonstrate a higher trust in automation (3,84). When they choose manual mode, they show less trust in automation (3,39). In general, participants felt that the vehicle was more often operated in manual mode.

In the main experiment, the design of the experiment will be changed – following and overtaking maneuvers will be carried in 2 different operation sessions. Participants will have a clear difference between overtaking and following maneuvers. Also, the experiment organizer will indicate for the cyclist when the vehicle is in automated mode, and when the car is in manual mode.

4.3 Conclusion

The results of the pilot-experiment show a need to change the design of the interaction scenarios. In the main experiment the number of rides will be increased to better capture the participants learning and in one ride only one vehicle maneuver will be performed, either following or overtaking. Additionally, before each ride the vehicle mode of operation, manual or automated, will be pre-specified for participants.

Pre-chosen attributes show a correlation with the subjective risk levels. Analysis shows that the relative distance may be the most influencing attribute, thus, for the main experiment, overtaking distance will be tested with two levels. Also, the barrier side of the road will not be used as it was designed to represent the parked cars and did not give a sufficient risk change. As there was no difference in subjective risk for different combination of attributes and no special reaction on the first met attributes, in the main experiment no special analysis will be held for the combinations.

For the main experiment the questionnaire will be reduced, as the time of completion was too long and pilot experiment showed that some parts were not changing and could be reduced. Also, self-reported attributes point out a new influencing attribute: characteristics of the vehicle, i.e. the vehicle size and noise, which will be included in the question about influencing parameters. Additionally, the scale used for the self-reported subjective risk will be increased to have a 5% step.

5 Main experiment results

5.1 Experiment setup.

The main experiment took 3 days and involved 25 participants. The number of male and female cyclists was almost equal (13 males; 12 females). As originally decided, all participants were from the same age group (mean=25,4; std.=1,3). Each participant took 30 minutes to complete the experiment. Each cyclist participated in 4 designed experiments and 1 familiarization route. Each scenario includes 2 rides and in one ride the participant experienced only 1 maneuver: following or overtaking. However, during 1 scenario participant experienced both: following maneuver and overtaking maneuver. During the overtaking maneuver, the vehicle follows the participant for 20 seconds and then proceeds to overtake. The overtaking distance had two values: 1,5 meters and 3,5 meters. The following distance was 3 meters. In all interaction scenarios, the vehicle operated in manual mode. However, for participants sometimes was pre-specified that the vehicle will be operated in automated mode. After each interaction scenario, participants mentioned how they perceive the interaction mode in this part of the route.

During the main-experiment, Lidars collect 5 measurements in 1 second and the GPS measured 5 position in 1 second, to have precise measurements of the passing stage of overtaking, which in some cases took only 3 seconds. The accuracy of the measurements was verified and shows that the measurement error of the Lidar is about 0-3 sm. The Figure 22 shows the measurement accuracy of the GPS position of the bicycle and the GPS accuracy of determining the position of the vehicle. The red dot indicates the GPS position captured by the equipment and the green dot (or orange dot in the case of a bicycle) points the actual position of the vehicle. GPS measurements of the bicycle position are also accurate. On other hand, the vehicle GPS does not show accurate lateral coordinates. However, in this research we apply local coordinates in the analysis and the position of the vehicle at the beginning of the route is fixed as a zero point. Thus, the discrepancy between the captured and real vehicle positions do not affect the accuracy of results.

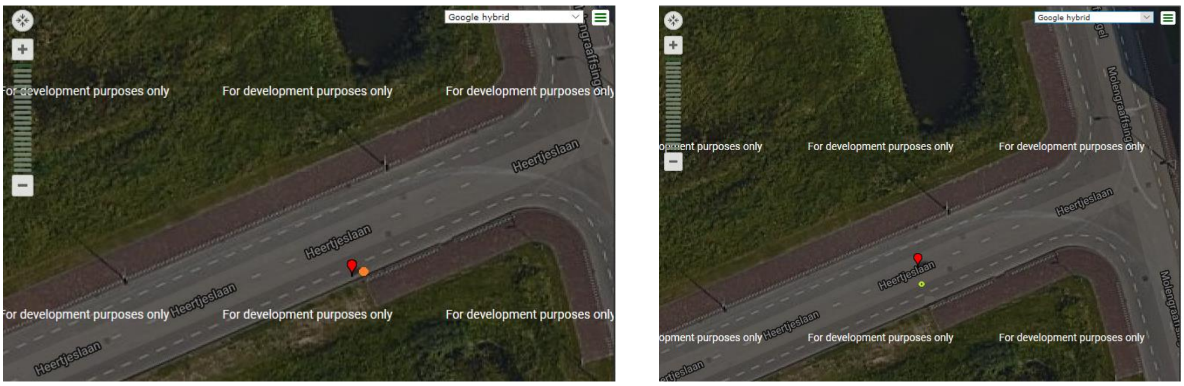


Figure 22: GPS accuracy (left picture: bicycle coordinates; right picture: vehicle coordinates)

During the experiment, the participant's level of Trust, Subjective and Objective Risks, the distance from the Bicycle to the Curb and the speed of the cyclist were measured. The Table 10 gives an overview of the number of observations collected.

Table 10: Number of observations

		Trust Level	***Subjective Risk Level***	***Objective Risk Level***	***Distance to the Curb***	***Speed***
			%	***Joules***	***Meters***	***Meter/Second***
Number of observations	Overall	242	242	80	222	100
	Per scenario: Automated following Automated overtaking Manual following Manual Overtaking	60	60	20	55	25
	Per scenario with a certain attribute of overtaking speed/distance	30	30	10	27	12
*Number of participants (25 participants did 10 rides; each participant did 4 scenarios)						

Questionnaires collected trust and subjective risk levels after each ride, while the objective risk level was calculated using the PDRF method for every 0,2 seconds of rides. A frequency of 0,2 seconds was chosen to capture the moment of overtaking, which takes less than 10 seconds. For the analysis, the route was divided in three sections. For the following maneuver, the beginning, middle and ending parts of the route were selected so that their ride duration was equal. For an overtaking maneuver, the beginning part represents the time before overtaking, the middle part corresponds to the overtaking maneuver and the ending part stands for the time when the cyclist rode without a vehicle. The Figure 23 shows the route separation in case of overtaking maneuver. For each part of the route the minimal, mean and maximum values of objective risk were also calculated.

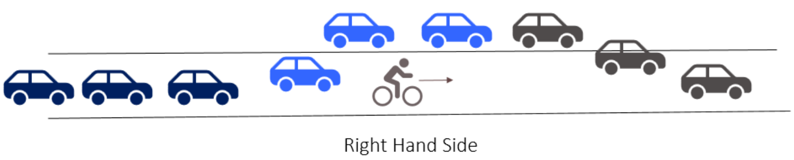


Figure 23: The Overtaking Maneuver

The Table 11 provides an overview of the weather conditions on each day of the experiment. The second day had the most comfortable weather conditions with moderate temperature and a cloudy sky. Results show that trust levels on the 2nd day were slightly higher and the subjective risk lower than other days. The boxplots of the dependence of parameters on the weather conditions are presented in the appendix.

Table 11: Overview of the weather conditions

Day	27 (1st day)	28 (2nd day)	29 (3rd day)
Weather	Bright Sun, +30	Clouds, +20	A little rain, +18

Male participants show higher trust. The level of subjective risk is the same for both genders. However, there is no high quartile on the boxplot of subjective risk for men, which means that data on subjective risk for men is more consistent and does not exceed the median value. Male participants also have a higher level of objective risk, which might be connected with higher trust and lower subjective risk level. As male participants perceive interactions to be less risky, they tend to be less cautious and ride closer to the car at a higher speed. The boxplots of the dependence of parameters on the gender of participants are presented in the appendix.

Although a preliminary analysis reveals the influence of weather conditions and gender of participants on the values of trust and risks, further analysis will not take these parameters into account. The experiment design verifies that in each group of scenarios there is an equal number of participants from every day of the experiment and each gender group. During the experiment, participants experienced 4 interaction scenarios and completed 10 rides. The analysis shows that there is no clear dependence of the level of Trust and Risks Levels on the amount of interaction with the vehicle. Following that, the further analysis will not take into account the ride number.

5.2 Attributes of the vehicle-cyclist interaction reported by participants.

During the experiment, participants reported attributes perceived as influencing on the subjective risk level. For automated overtaking, manual overtaking and manual following scenarios the most influencing attributes are distance to the vehicle, vehicle characteristics and speed of the vehicle. For the Automated Following scenario additional importance was given to the fact that vehicle had an automated driving mode. The Figure 24 shows the share of the attributes reported as an influencing for all interaction scenarios.

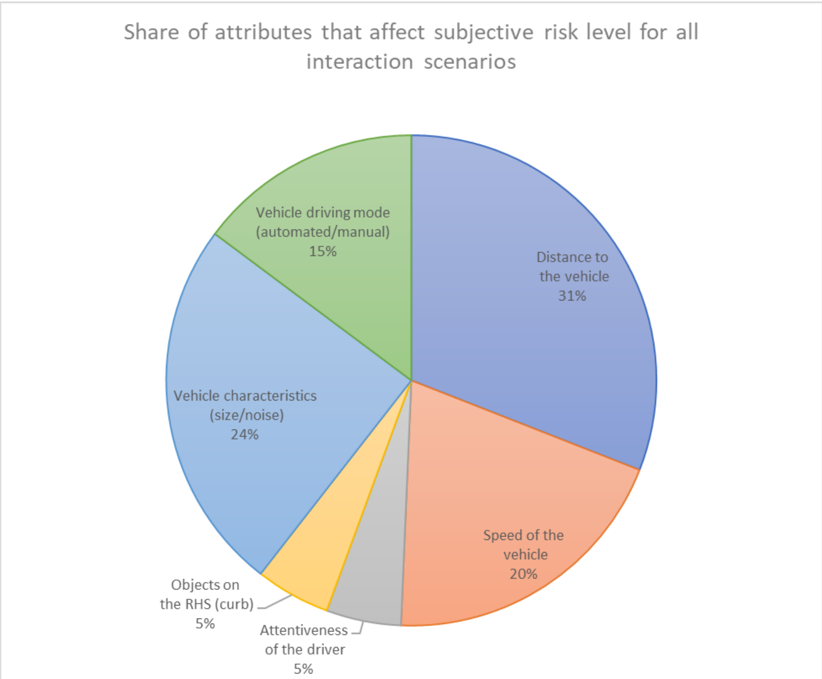


Figure 24: Subjective Risk Level Attributes

5.3 Preliminary analysis of the interaction scenarios.

5.3.1 Statistical analysis of the interaction scenarios

The experiment includes 4 interaction scenarios: automated following, automated overtaking, manual following and manual overtaking. Each of these scenarios was analyzed in terms of trust levels, subjective and objective risk levels, speed of cyclists and distance of cyclist to the curb. The boxplot analysis eliminates the interactions between parameters interesting for further analysis. For all mentioned below interactions between parameters were conducted statistical tests presented in the appendix. The table below mentioned statistical tests that approve statistical significance of the parameter interactions.

Table 12: Preliminary statistical analysis of the interaction scenarios

Statistical Test	***Null Hypothesis***	***Bonferroni Correction (BC)***	***P-Value after BC***	***Conclusion***
The Wilcoxon Test	*H_0^1: There is no difference in the subjective risk level of the overtaking maneuver and the subjective risk level of the following maneuver.*	a=0,01	p=0,001	There is evidence that the subjective risk varies per maneuver.
The Wilcoxon Test	*H_0^2: There is no difference in the objective risk level of the overtaking maneuver and the objective risk level of the following maneuver.*	a=0,0125	Mean objective risk: p=0,0014 Max objective risk: p=0,000	There is evidence that the objective risk value varies per maneuver.

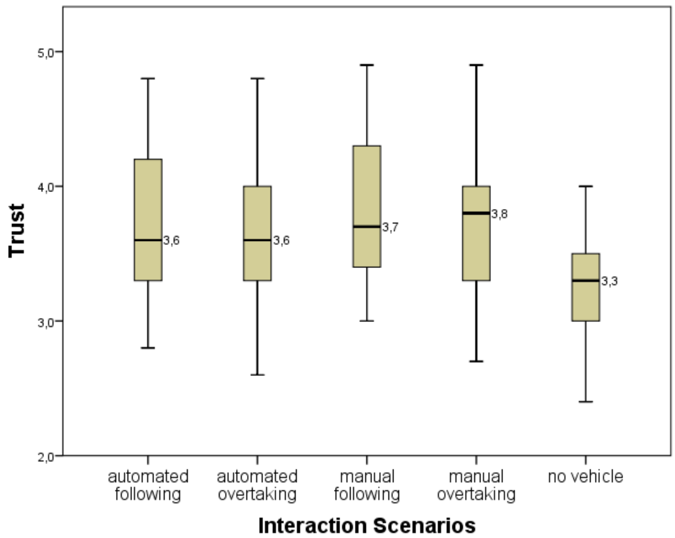


Figure 25: Dependence of trust levels on the Interaction Scenarios

Boxplot (Figure 25) shows that the manual driving mode has a higher level of trust than the automated driving mode. In automatic mode both the overtaking maneuver and the following maneuver have the same level of trust, while the manual overtaking maneuver has a higher level of trust than the manual following maneuver. The highest level of trust is found in the manual overtaking scenario. However, the manual following scenario and the automated following scenarios have high values of the upper quartile, which indicates that some participants have experienced greater trust in this scenario.

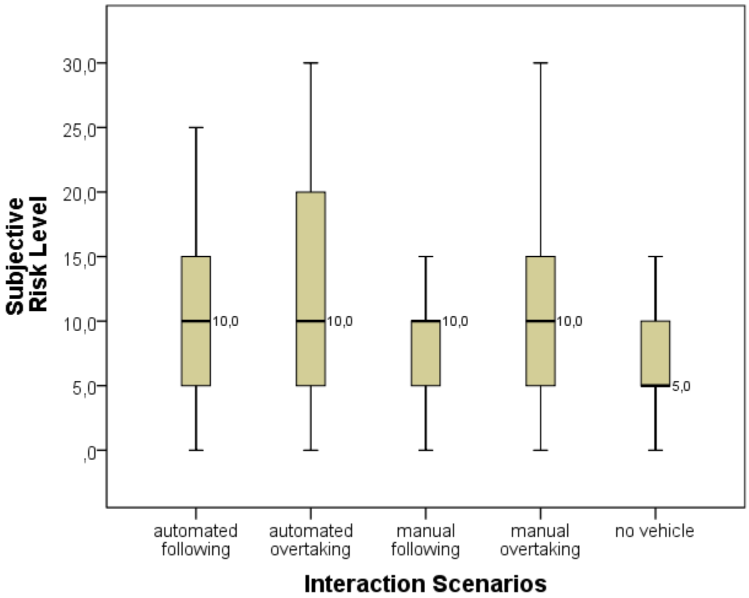


Figure 26: Dependence of the Subjective Risk Level on the Interaction Scenarios

An analysis of the dependency of the level of Subjective Risk on Interaction Scenarios (Figure 26) shows that all interaction scenarios have the same level of subjective risk. However, scenarios with driving in the automated mode have higher upper quartiles than scenarios with driving in the manual mode, which shows less coherence between the results of the risk level and indicates that some participants experienced an even higher level of Subjective Risk. In addition to changes in the Risk Level depending on the driving mode, the driving maneuvers also influence the Risk Level: the overtaking maneuvers in both driving modes have higher upper quartiles and higher whiskers than the following maneuvers. There is a statistical evidence that the subjective risk level of the following maneuver is less than the subjective risk level of overtaking maneuver. Overall, the scenario with the manual following maneuvers have the lowest level of Subjective Risk.

As discussed above, to calculate the objective risk values, the initial route was divided in 3 parts. The overtaking maneuver use the middle part in its analysis as in this part of the route the maneuver takes place. For the following maneuver, it is necessary to choose a part of the route for future analysis based on the values of objective risk, distance to the curb and speed of the cyclist.

The minimum objective risk value is 0 for all scenarios. The following maneuver has the highest mean and maximum values of Objective Risk in the last part of the route (Figure 27). For the following maneuver, the minimum and mean distances to the curb reach the highest values in the middle of the route, while the maximum distance to the curb reaches the highest value at the end part of the route. The Mean and Minimum Speeds reach the highest values in the middle of the route, while the maximum speeds reach the highest values at the end part of the route.

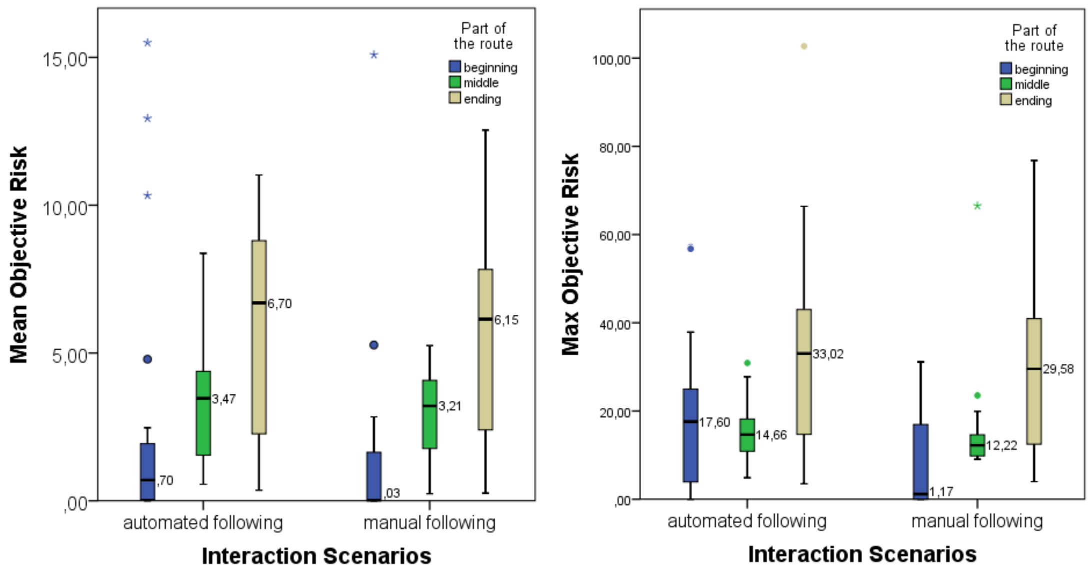


Figure 27: Dependence of the Mean Objective Risk and Max Objective Risk on the Interaction Scenarios

Table 13: Following Maneuver Analysis Results

	Beginning	***Middle***	***Ending***
Min Objective Risk	0	0	0
Mean Objective Risk			Highest Value
Max Objective Risk			Highest Value
Min Distance		Highest Value	
Mean Distance		Highest Value	
Max Distance			Highest Value
Min Speed		Highest Value	
Mean Speed		Highest Value	
Max Speed			Highest Value

The middle part of the route was selected for future analysis of the following maneuver. There are following and overtaking maneuvers on this part of the route and the middle part represents the general behavior of cyclists. The ending part of the route may give biased results, as cyclists are sure that the route will end soon.

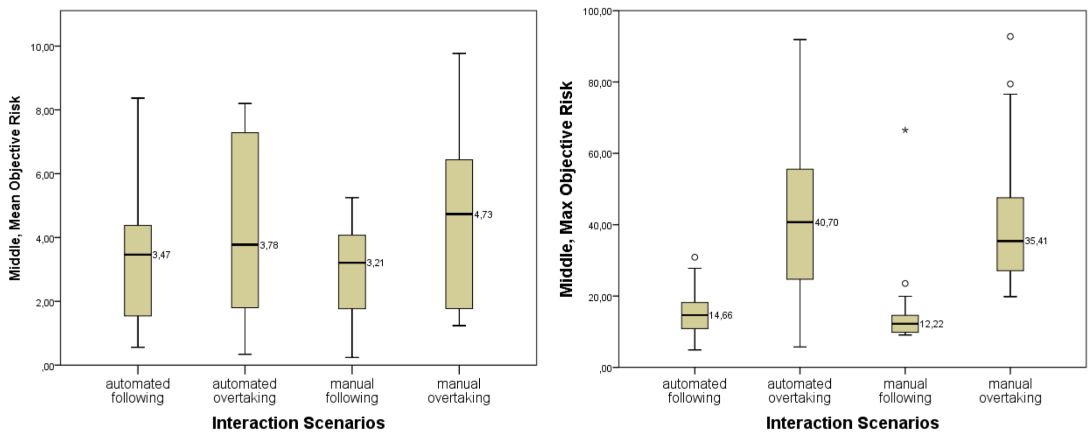


Figure 28: Dependence of the Mean Objective Risk and Max Objective Risk on the Interaction Scenarios

The boxplot of the objective risk versus interaction scenarios (Figure 28) shows that in the following maneuver, the automated mode has higher mean and maximum values of the objective risk level than the manual mode. For the overtaking maneuver, the maximum objective risk has higher values in driving in the automated mode than in driving in the manual mode, while the mean objective risk has higher values for overtaking in manual overtaking scenario than for automated overtaking scenario. The following maneuver has lower mean and maximum objective risks than the overtaking maneuver and there is a statistical evidence that the objective risk for the following maneuver is less than the objective risk for the overtaking maneuver. Changes in objective risk may be related to the changes in the distances to the curb and the speed of the cyclist.

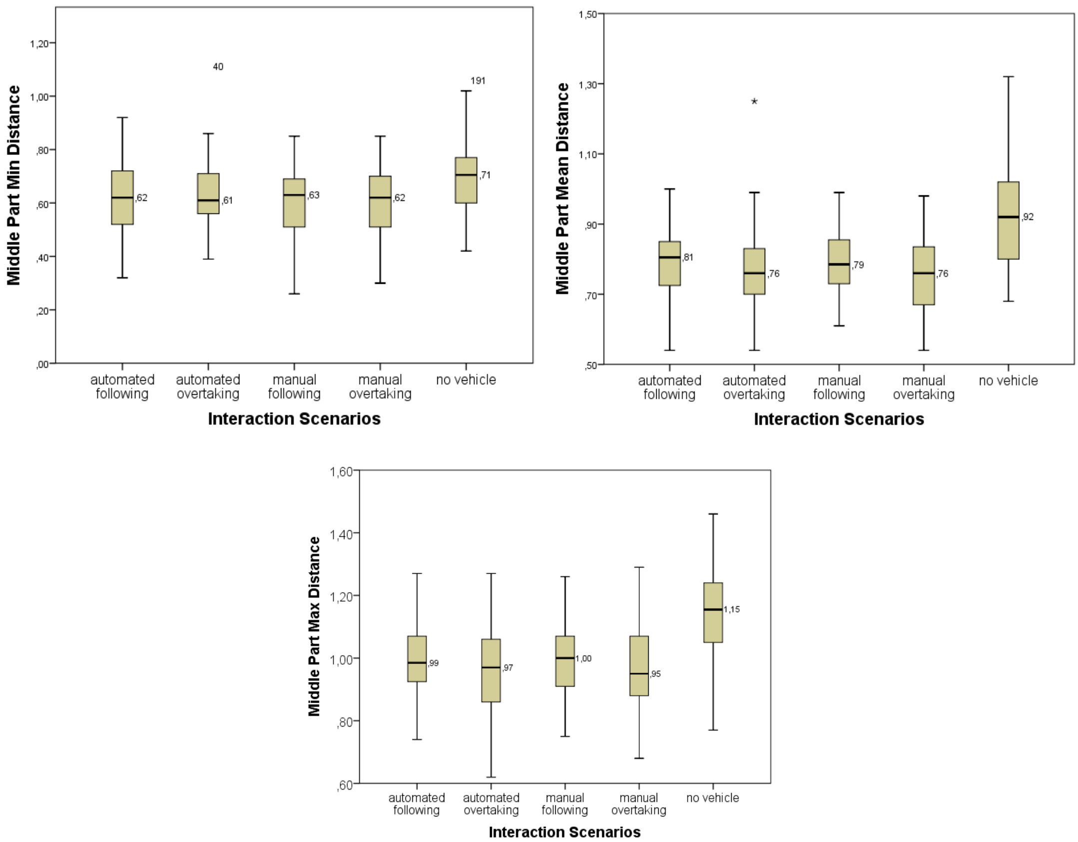


Figure 29: Dependence of the Min, Mean, Max Distances on the Interaction Scenarios

The distances to the curb are almost the same for all interaction scenarios (Figure 29). In overtaking scenarios, the minimum, maximum and mean distances are slightly lower than in the following maneuver scenarios. Manual driving scenarios have a slightly higher minimum distance than automated driving scenarios. The mean distance in the automated driving mode has higher value than the mean distance in the manual driving mode.

The Mean Speed has higher values for the following maneuvers than for overtaking maneuvers, while the Maximum speed has higher values for the overtaking maneuvers than for the following maneuvers (Figure 30). Furthermore, the maximum speed has higher values for driving in automated mode than for manual driving.

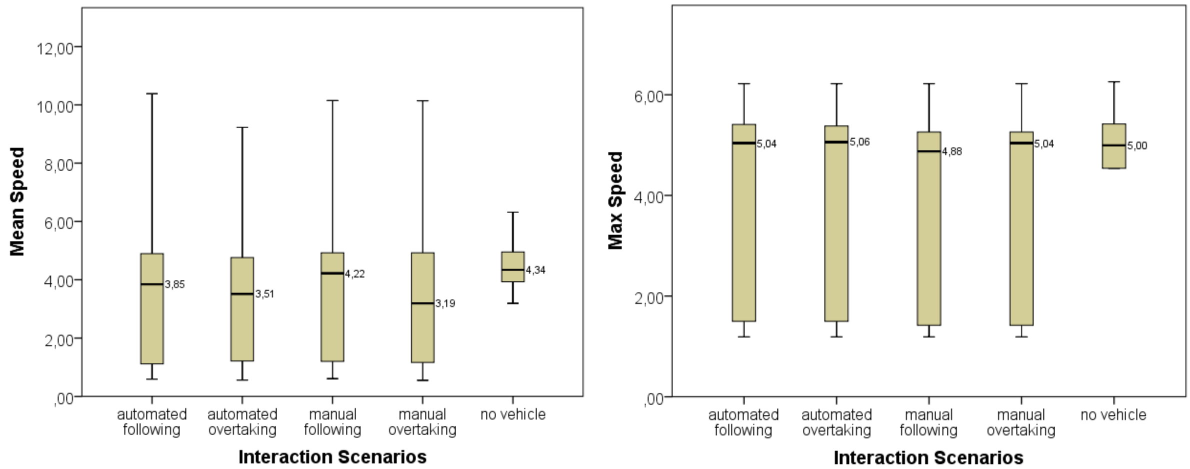


Figure 30: Dependence of the Mean, Max Speeds on the Interaction Scenarios

5.3.2 Statistical analysis of the attributes.

Table 14: Preliminary statistical analysis of the attributes of the interaction scenarios

Statistical Test	**Null Hypothesis**	**Bonferroni Correction (BC)**	**P-Value after BC**	**Conclusion**
The Wilcoxon Test	*H_0^3: There is no difference between the mean values of the Subjective Risk for the overtaking with distance of 1,5m and overtaking with distance of 3,5m for driving in automated mode.*	a=0,0125	p=0,03	There is statistical evidence that the subjective risk for the overtaking with 3,5 m is lower than the subjective risk for overtaking with the 1,5 m.
T-Test	*H_0^4: There is no difference between the mean values of the Subjective Risk for the overtaking with distance of 1,5m and overtaking with distance of 3,5m for driving in manual mode.*	a=0,0125	p=0,003	There is statistical evidence that the subjective risk for the overtaking with 3,5 m is lower than the subjective risk for overtaking with the 1,5 m.
The Wilcoxon Test	*H_0^5: There is no difference between the mean distance to the curb values for the overtakings with the distance of 1,5m and overtakings with the distance of 3,5m.*	a=0,0125	p=0,009	There is statistically significant evidence that the mean distance to the curb for the overtaking with 1,5 m is lower than the mean distance to the curb when overtaking with 3,5m.

Besides interaction scenarios, the experiment includes speed and distance as attributes for overtaking. Each attribute has two levels. This section discusses the dependence of trust and risks during scenarios of manual overtaking and automated overtaking on the speed of overtaking and the distance of overtaking.

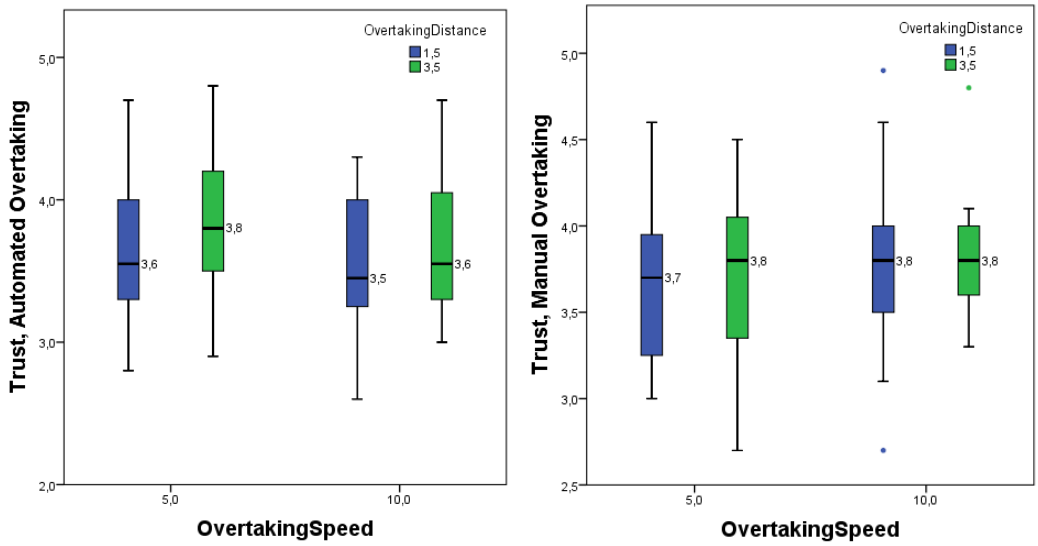


Figure 31: Dependence of the Trust Level on Overtaking Speed and Overtaking Distance

Figure 31 shows that trust level in the overtaking maneuver with distance of 3,5 m has a slightly higher level of trust than overtaking with a distance of 1,5 m. In automated overtaking scenarios, overtaking at a lower speed has a higher level of trust. In manual driving, a higher speed during overtaking have higher trust level.

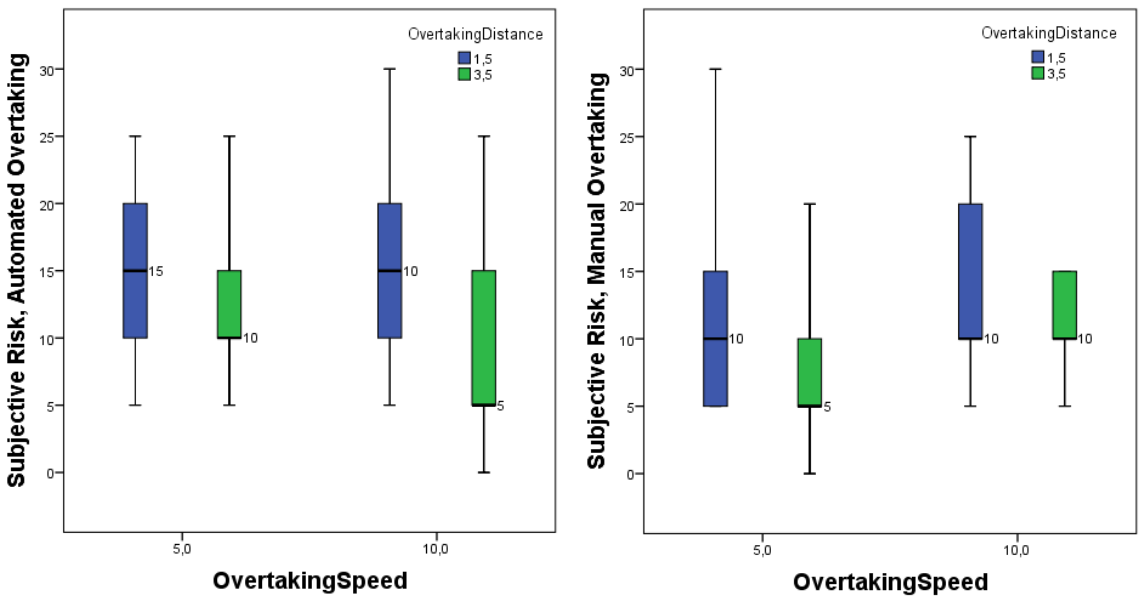


Figure 32: Dependence of the Subjective Risk Level on Overtaking Speed and Overtaking Distance

The Boxplot (Figure 32) shows that the subjective risk is higher for overtaking maneuvers with a distance of 1,5 m and the statistical evidence approve that the subjective risk for the overtaking with 3,5 m is lower than the subjective risk for overtaking with the 1,5 m. For driving in automated mode, overtaking at lower speed has a higher level of subjective risk than overtaking at a higher speed. The preference for a higher overtaking speed can be explained by comparing times of interactions. Participants may perceive shorter interaction times as safer interactions. Furthermore, analysis shows that overtaking with a low speed in automated mode perceived by participants as riskier than overtaking in manual mode.

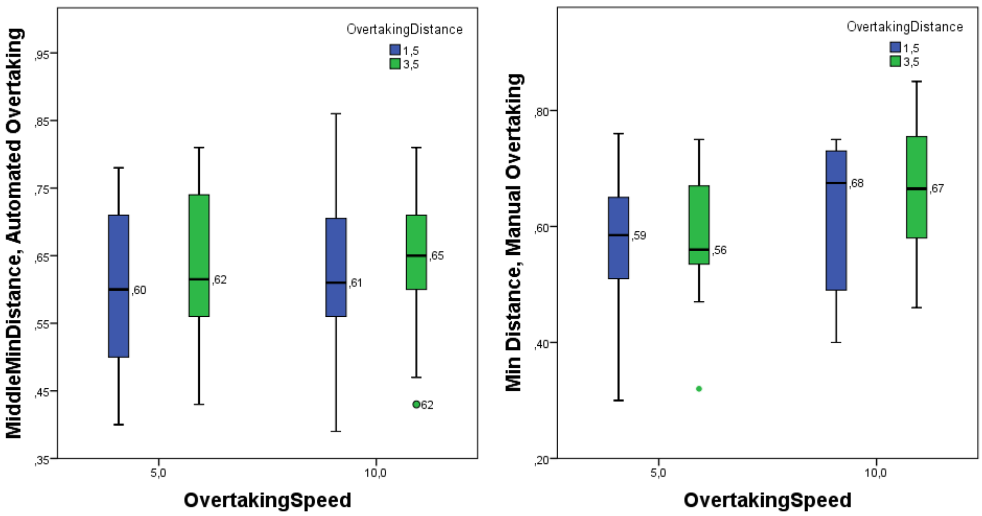


Figure 33: Dependence of the Cyclist Distance to the Curb on Overtaking Speed and Overtaking Distance

The minimum distance has slightly higher values for overtaking maneuvers at a higher speed than for overtaking maneuvers at a lower speed for both vehicle modes (Figure 33). In automated scenario, overtaking with a distance of 3,5 m has a lower minimum distance value than overtaking with a distance of 1,5 m. In manual overtaking scenario, the minimum distance to the curb has higher values when overtaking with a distance of 1,5 meters.

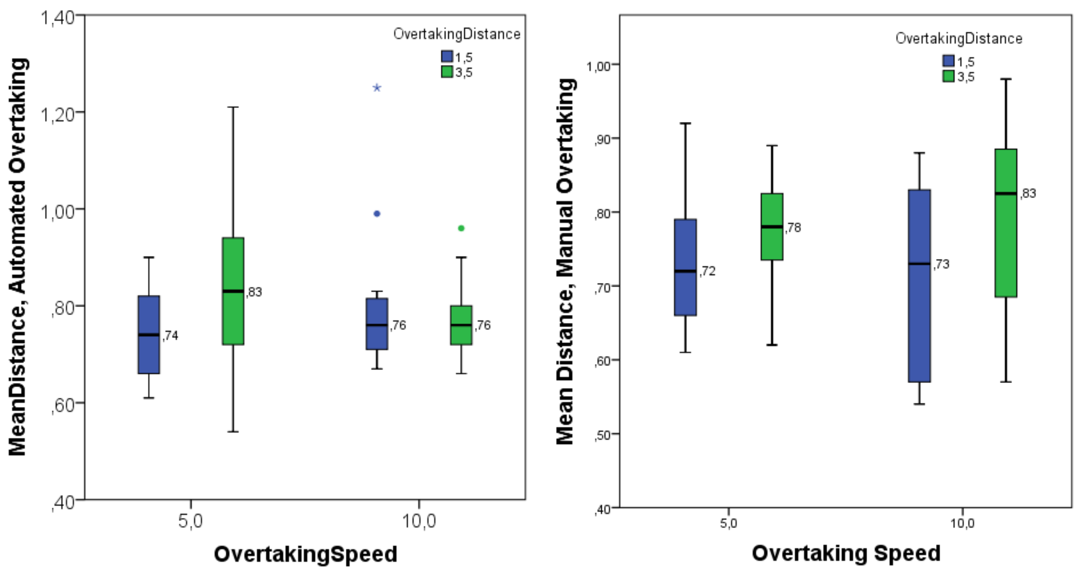


Figure 34: Dependence of the Cyclist Distance to the Curb on Overtaking Speed and Overtaking Distance

The Mean Distance to the Curb has higher values in overtaking scenarios with an overtaking distance of 3,5 meters for both modes of vehicle operation and statistical test approve that the mean distance to the curb for the overtaking with 1,5 m is lower than the mean distance to the curb when overtaking with 3,5 m. For overtaking in the manual driving mode, the overtakings at a higher speed have higher mean distance values (Figure 34).

5.3.3 Statistical analysis of the vehicle maneuvers for the same relative distances.

The preliminary analysis shows that there is dependency of trust, subjective risk and objective risk on the relative distance between the vehicle and the cyclist. This section presents an analysis of the data from the interaction scenarios of overtaking maneuvers with 3,5 m and following maneuvers with 3 m.

The Trust level has slightly higher values for the overtaking maneuver that for the following maneuver. Also, driving in manual mode have slightly higher trust level than driving in automated mode. All interaction scenarios have same level of subjective risk. However, the manual following scenario have no higher quartile values. The automated following and automated overtaking have higher whiskers, which indicates that the automated driving mode may have a higher subjective risk level.

The max objective risk for overtaking maneuvers has much higher mean values than for following maneuvers. The automated mode has a higher objective risk values than manual mode. However, the boxplot of automated overtaking has big quartile and long whiskers, showing the incoherence in max objective risk values.

The Wilcoxon text for max objective risk values shows with the p-value=0,001 that the null hypothesis can be rejected. The null hypothesis is set as H_0^6: *There is no significant difference between the mean values of the max Objective Risk for the following and overtaking maneuvers.* After the application of the Bonferroni correction (0,0125) there is still statistically significant evidence that the Objective Risk of the following maneuver is lower than the Objective Risk of overtaking maneuver.

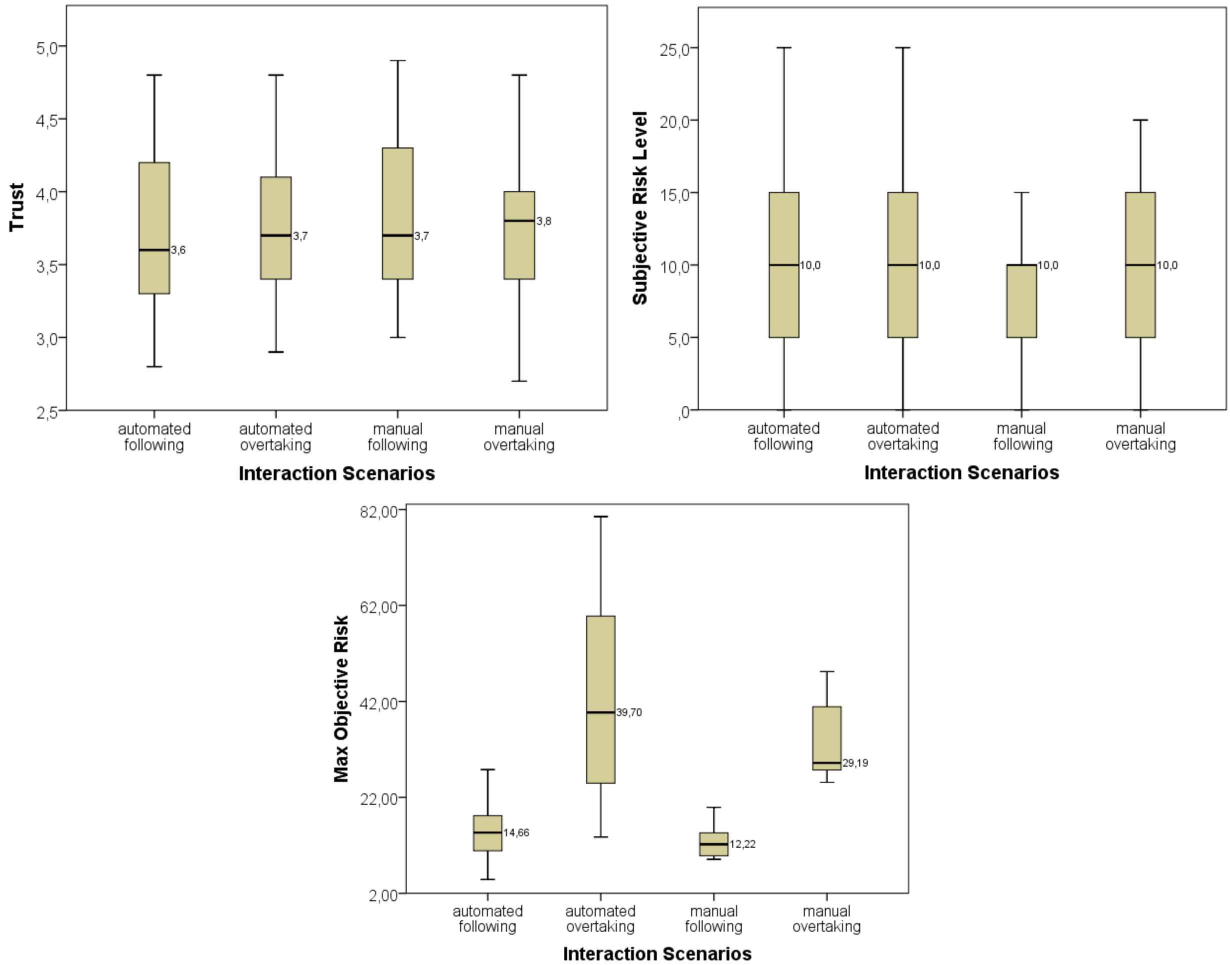


Figure 35: Dependence of the Trust, Subjective Risk and Max Objective Risk on the Interaction Scenarios

5.3.4 Statistical analysis of the influence of the right hand side objects

Table 15: Preliminary statistical analysis of the influence of the Right Hand side objects

Statistical Test	Null Hypothesis	Bonferroni Correction (BC)	P-Value after BC	Conclusion
The Wilcoxon test	H_0^7: There is no significant difference between the mean values of the Distance to the Curb for the Grass on the side of the road and the Asphalt on the side of the road.	a=0,025	p=0,000	The Distance to the Curb of cyclist riding on the side with the curb (asphalt) is higher than the Distance to the Curb of the cyclist cycling on the side of the green grass.
The Wilcoxon test	H_0^8: There is no significant difference between the mean values of the Cyclist Speed for the Grass on the side of the road and the Asphalt (Curb) on the side of the road.	a=0,025	p=0,000	The mean values of the Cyclist Speed are higher in the case of the grass on the RHS than in the case of the Curb on the RHS.
The Wilcoxon test	H_0^9: There is no difference between the mean values of the Relative Distance on the side of the road with the Green Grass and the side of the road of the Curb.	a=0,025	p=0,025	The relative distance on the side of curb is lower than the relative distance on the side of grass.
The Wilcoxon test	H_0^{10}: There is no difference between the mean values of the Trust Level when cycling with the asphalt on the RHS and Trust level when cycling when the green grass is on the RHS.	a=0,025	p=0,000	The trust level for driving with the asphalt on the RHS is higher than the trust level for cycling with the grass on the RHS.

One of the attributes of the experiment is the right-hand side. This attribute has two values: the green grass side and the asphalt side (Figure 36).

Figure 36: Right Hand Side Objects

The statistical analysis shows that the Distance to the Curb of cyclist riding on the side with the curb (asphalt) is higher than the Distance to the Curb of the cyclist cycling on the side of the green grass. The mean values of the Cyclist Speed are higher in the case of the grass on the RHS than in the case of the Curb on the RHS. The relative distance on the side of curb is lower than the relative distance on the side of grass. The trust level for driving with the asphalt on the RHS is higher than the trust level for cycling with the grass on the RHS.

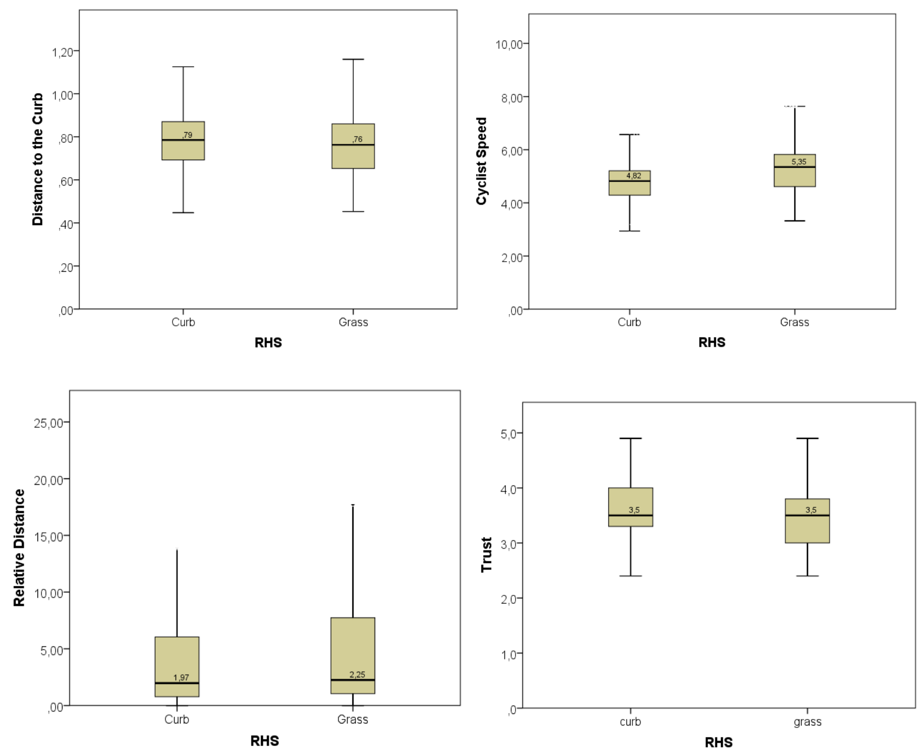


Figure 37: Dependence of the Distance to the Curb, Cyclist Speed, Relative Distance and Trust on the RHS object. Dependence of the Relative Distance on the RHS object

5.4 Correlations analysis

Trust and subjective risk values are discrete, being collected once after each ride. Objective Risk, cyclist speed, lateral distance to the curb, relative distance and relative speed are continuous data, being collected for every 0,2 sec of each ride. The conversion of continuous to discrete data may affect the validity of results. Two correlation analyses for non-parametric data sets (Spearman correlation) were conducted. The correlation analysis null hypothesis was H_o^1: *All parameters used in the correlation analysis are independent of each other.* The correlation matrix for the discrete data set is present in the appendix. There is a statistically significant negative association between subjective risk level and vehicle overtaking speed (p=0,005, r_s= -0,268), which indicates that an increase of overtaking distance is associated to an increase in subjective risk levels. However, after application of Bonferroni correction (corrected a=0,003) the null hypothesis could not be rejected. The strong negative correlation (p=0,000 r_s=-0,428 a=0,001) is between the trust Level and the subjective risk level: with an increase in Trust Level the Risk level decreases. Furthermore, there is strong positive correlation between trust level and objective risk (p=0,000 r_s=+0,487 a=0,001) for mean and max objective risk, and a mean negative correlation (p=0,000 r_s=-0,324 a=0,001) between the trust and max distance to the curb.

The Spearman Correlation Matrix for the continuous data ,presented on Table 16, shows that there is a strong negative correlation between the Objective Risk and the Relative Distance (p=0,000, r_s=-0,778 a=0,005) and a strong positive correlation observed between the Relative Distance and the Relative Speed (p=0,000, r_s=0,574 a=0,005). The mean negative correlation is between the relative speed and Objective Risk (p=0,000, r_s=-0,28 a=0,005) and between the Distance to the Curb and Objective Risk (p=0,000, r_s=-0,11 a=0,005). A weak negative correlation appears between the Relative Distance and the Distance to the Curb (p=0,001, r_s=-0,077 a=0,005) and between the Relative Speed and the Distance to the Curb (p=0,002, r_s=-0,068 a=0,005).

Table 16: Spearman Correlation Matrix for continuous data

			Objective Risk	Distance to the Curb	Relative Distance	Cyclist Speed	Relative Speed
Spearman's rho	Objective Risk	Correlation Coefficient	1,000	-,110**	-,778**	-,033	-,280**
		Sig. (2-tailed)		,000	0,000	,136	,000
		N	1998	1998	1998	1998	1998
	Distance to the Curb	Correlation Coefficient	-,110**	1,000	-,077**	-,035	-,068**
		Sig. (2-tailed)	,000		,001	,118	,002
		N	1998	1998	1998	1998	1998
	Relative Distance	Correlation Coefficient	-,778**	-,077**	1,000	,053*	,574**
		Sig. (2-tailed)	0,000	,001		,018	,000
		N	1998	1998	1998	1998	1998
	Cyclist Speed	Correlation Coefficient	-,033	-,035	,053*	1,000	-,013
		Sig. (2-tailed)	,136	,118	,018		,574
		N	1998	1998	1998	1998	1998
	Relative Speed	Correlation Coefficient	-,280**	-,068**	,574**	-,013	1,000
		Sig. (2-tailed)	,000	,002	,000	,574	
		N	1998	1998	1998	1998	1998

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

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

5.5 Participants learning analysis

Automated driving is new. Cyclists may have less trust on automated vehicle scenarios due to the lack of familiarization. It must be checked if an increase of the interaction time leads to a higher trust. Trust, subjective risk and objective risk are non-parametric data. To see changes over time, the Friedman test was applied. The experiment was designed in a way that for the same participant the same interaction scenario will be repeated in a 1st and 3rd ride or in a 2nd and 4th ride, which means that inside the interaction scenarios the 1st and 2nd ride was done by different participants. The Friedman test conduct an analysis for every interaction scenario and for two groups of participants. All results of the Friedman test are presented in the appendix. The Friedman test shows no difference in trust, subjective risk Level and objective risk in 10 rides time.

5.6 Generalized Linear Mixed Model

To get insights on the relationship between non-parametric target parameters of trust, subjective risk, objective risk and independent variables, the Generalized Linear Mixed Model (GLMM) was applied. With respect to subjective risk and trust, one model was built for the all interaction scenarios and another model was built for the overtaking scenarios with overtaking attributes. With respect to objective risk, a GLMM was built. In the last model, trust and Subjective Risk were not included as parameters to avoid violation of continuous trust data with discrete trust and subjective risk data.

Besides including fixed effects, the Linear Mixed Models can include random effects. Each model was tested in four conditions: random effects, to see which random effect has significant influence; influencing random effects; no random effect; and random intercept. The Akaike Corrected and Bayesian criterion were compared between models and the one with the lowest information criterion (and thus better model fit) was further analyzed. In all cases, random intercepts were further analyzed. All completed GLMM and comparison of the models fits for each case are presented in the appendix. This section presents the analysis of the chosen models.

5.6.1 The Generalized Linear Mixed Model for the subjective risk

Table 17: Input parameters for the GLMM for the subjective risk

	Fixed Effects	***Random Effects***
Subject: Participants number	Gender	Random Intercept
Repeated measures: Rides number	RHS	
Target: Subjective Risk Level	Interaction Scenarios	
	Max Objective Risk	
	Max Cyclist Speed	
	Mean Distance to the Curb	
	Trust	

The GLMM originally considered max objective risk, max cyclist speed, mean distance to the curb and trust as random parameters. This model shows no statistically significant intercepts for random parameters. The model with only a random intercept shows the best model fit (Akaike Corrected Criterion = 604,688; Bayesian=628,634) and was chosen for further analysis.

The fixed effects analysis shows the statistically significant (p=0,000) relationship between trust level and the subjective risk level with a magnitude of -6,690. A trust improvement in 1 unit leads to a reduction of predicted subjective risk in -6,690. In other words, two participants with the difference in subjective risk level of 1 unit have a difference in trust level of 6,690. Furthermore, the model shows a statistically significant (p=0,042 and p=0,039) relationship between interaction scenarios and subjective risk. The magnitude of automated following is equal to 5,521, while magnitude of the automated overtaking is 5,930. Pairwise comparison shows the statistically significant (p=0,033) relationship between automated overtaking and manual following with the magnitude of 2,744. The regression equation for this model is as follows:

$S=39,942 - 6,690y + 5,521x + 5,930z$

Where mean of the Subjective Risk = 39,942 for the participant with trust=0 and interaction scenario with no vehicle. According to this model the Trust is the strongest individual predictor in the model.

Table 18: Variables of the regression equation of the GLMM for the subjective risk

Variables	***Description***
S	Subjective risk
Y	Trust
X	1 for interaction with automated following and 0 for interaction with no vehicle
Z	1 for interaction with automated overtaking and 0 for interaction with no vehicle.

Model Term	Coefficient ▼	Std.Error	t	Sig.	95% Confidence Interval	
					Lower	Upper
Intercept	39,942	8,677	4,603	,000	22,700	57,183
Trust	-6,690	1,379	-4,852	,000	-9,430	-3,950
Gender=female	-0,702	2,831	-0,248	,805	-6,326	4,923
Gender=male	0,000[a]					
RHS=curb	-0,539	0,825	-0,654	,515	-2,178	1,099
RHS=grass	0,000[a]					
MaxObjectiveRisk	0,014	0,024	0,581	,563	-0,034	0,062
MeanDistancetotheCurb	-8,384	5,736	-1,462	,147	-19,782	3,013
MaxCyclistSpeed	-0,213	0,912	-0,234	,816	-2,025	1,598
InteractionScenarios=automated following	5,521	2,671	2,067	,042	0,214	10,828
InteractionScenarios=automated overtaking	5,930	2,825	2,099	,039	0,317	11,543
InteractionScenarios=manual following	3,186	2,790	1,142	,257	-2,358	8,729
InteractionScenarios=manual overtaking	4,265	2,844	1,499	,137	-1,387	9,917
InteractionScenarios=no vehicle	0,000[a]					

Probability distribution:Normal
Link function:Identity

[a]This coefficient is set to zero because it is redundant.

Figure 38: Fixed effects

Interaction Scenarios Pairwise Contrasts	Contrast Estimate ▼	Std. Error	t	df	Adj. Sig.	95% Confidence Interval	
						Lower	Upper
automated following - automated overtaking	-0,409	1,290	-0,317	89	0,752	-2,973	2,155
automated following - manual following	2,335	1,208	1,933	89	0,056	-0,065	4,735
automated following - manual overtaking	1,256	1,379	0,911	89	0,365	-1,484	3,996
automated following - no vehicle	5,521	2,671	2,067	89	0,042	0,214	10,828
automated overtaking - automated following	0,409	1,290	0,317	89	0,752	-2,155	2,973
automated overtaking - manual following	2,744	1,265	2,169	89	0,033	0,231	5,257
automated overtaking - manual overtaking	1,665	1,125	1,479	89	0,143	-0,571	3,901
automated overtaking - no vehicle	5,930	2,825	2,099	89	0,039	0,317	11,543
manual following - automated following	-2,335	1,208	-1,933	89	0,056	-4,735	0,065
manual following - automated overtaking	-2,744	1,265	-2,169	89	0,033	-5,257	-0,231
manual following - manual overtaking	-1,079	1,342	-0,804	89	0,423	-3,745	1,587
manual following - no vehicle	3,186	2,790	1,142	89	0,257	-2,358	8,729
manual overtaking - automated following	-1,256	1,379	-0,911	89	0,365	-3,996	1,484
manual overtaking - automated overtaking	-1,665	1,125	-1,479	89	0,143	-3,901	0,571
manual overtaking - manual following	1,079	1,342	0,804	89	0,423	-1,587	3,745
manual overtaking - no vehicle	4,265	2,844	1,499	89	0,137	-1,387	9,917
no vehicle - automated following	-5,521	2,671	-2,067	89	0,042	-10,828	-0,214
no vehicle - automated overtaking	-5,930	2,825	-2,099	89	0,039	-11,543	-0,317
no vehicle - manual following	-3,186	2,790	-1,142	89	0,257	-8,729	2,358
no vehicle - manual overtaking	-4,265	2,844	-1,499	89	0,137	-9,917	1,387

Significant contrasts are shaded gold. The least significant difference adjusted significance level is .05.

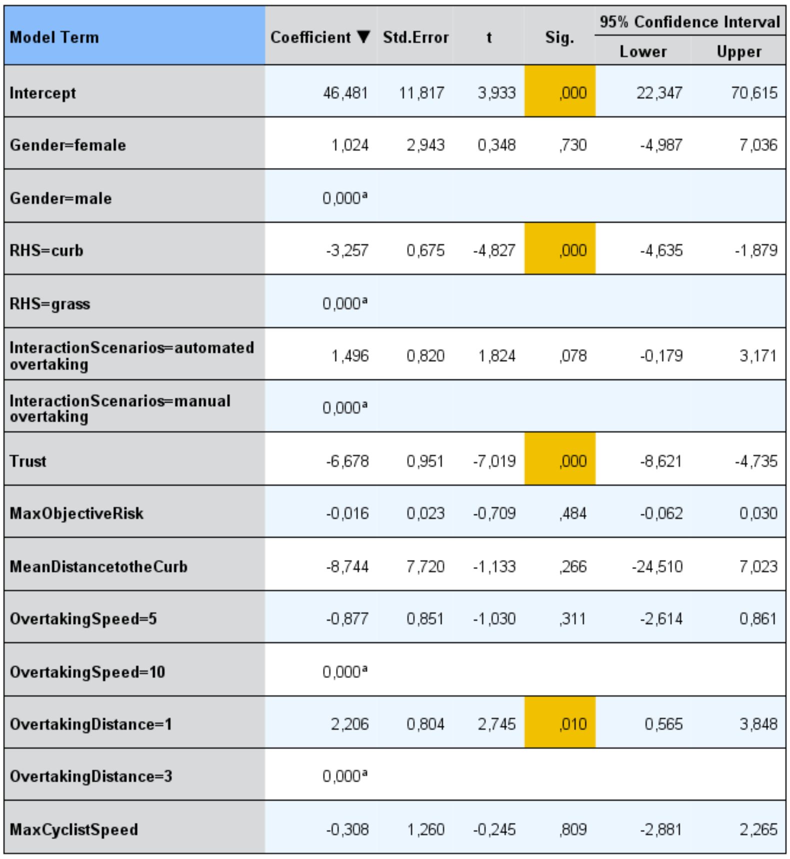
Figure 39: Pairwise comparison

5.6.2 The Generalized Linear Mixed Model for the subjective risk in overtaking scenarios

Table 19: Input parameters to the GLMM for the subjective risk in overtaking scenarios

	Fixed Effects	***Random Effects***
Subject: Participants number	Gender	Random intercept
Repeated measures: Rides number	RHS	Mean Distance to the Curb*
Target: Subjective Risk Level	Interaction Scenarios (Manual Overtaking and Automated Overtaking)	
	Max Objective Risk	
	Max Cyclist Speed	
	Mean Distance to the Curb	
	Trust	
	Overtaking Speed	
	Overtaking Distance	

The GLMM model considered max objective risk, max cyclist speed, mean distance to the curb, trust, overtaking speed and overtaking distance as random parameters. This model shows that the mean distance to the curb as a random parameter has statistically significant intercept. However, the model with only a random intercept shows the best model fit (Akaike Corrected Criterion =217,132; Bayesian=220,742) and was chosen for further analysis.



Model Term	Coefficient ▼	Std.Error	t	Sig.	95% Confidence Interval Lower	95% Confidence Interval Upper
Intercept	46,481	11,817	3,933	,000	22,347	70,615
Gender=female	1,024	2,943	0,348	,730	-4,987	7,036
Gender=male	0,000ᵃ					
RHS=curb	-3,257	0,675	-4,827	,000	-4,635	-1,879
RHS=grass	0,000ᵃ					
InteractionScenarios=automated overtaking	1,496	0,820	1,824	,078	-0,179	3,171
InteractionScenarios=manual overtaking	0,000ᵃ					
Trust	-6,678	0,951	-7,019	,000	-8,621	-4,735
MaxObjectiveRisk	-0,016	0,023	-0,709	,484	-0,062	0,030
MeanDistancetotheCurb	-8,744	7,720	-1,133	,266	-24,510	7,023
OvertakingSpeed=5	-0,877	0,851	-1,030	,311	-2,614	0,861
OvertakingSpeed=10	0,000ᵃ					
OvertakingDistance=1	2,206	0,804	2,745	,010	0,565	3,848
OvertakingDistance=3	0,000ᵃ					
MaxCyclistSpeed	-0,308	1,260	-0,245	,809	-2,881	2,265

Figure 40: Fixed Effects

There is a statistically significant (p=0,000) relationship between right hand side object and the Subjective Risk Level with a magnitude of -3,257. The Grass Side has higher Risk Level comparing to the Curb Side. Moreover, there is a statistically significant (p=0,000) relationship between Trust and Subjective Risk Level with a magnitude of -6,678. The improvement of Trust in 1 unit leads to reduction of the predicted Subjective Risk on -6,678. If there are two participants with the difference in Subjective Risk level of 1 unit their trust level will be different on 6,678.

There is a statistically significant (p=0,010) relationship between Overtaking Distance and Subjective Risk Level with a magnitude of 2,206. The closer Overtaking Distance of 1,5 m has higher risk Level than the overtaking Distance of 3,5 m. The regression equation for this model is as follows:

$S=46{,}481 - 3{,}257\,x - 6{,}678\,y + 2{,}206\,z$

Where 46,481 is a mean value of the Subjective Risk Level for the participant with a trust=0 riding on the grass side of the road and experiencing overtaking scenario with the 3,5m lateral distance. According to this model the Trust is the strongest individual predictor in the model.

Table 20: Variables of the regression equation of the GLMM for the subjective risk in overtaking scenarios

Variables	***Description***
X	1 if its curb and 0 if its green grass
Y	Trust
Z	1 if its 1,5m overtaking and 0 if its 3,5 m overtaking

5.6.3 The Generalized Linear Mixed Model for the trust

Table 21: Input parameters to the GLMM for the trust

	Fixed Effects	***Random Effects***
Subject: Participants number	Gender	Random intercept
Repeated measures: Rides number	RHS	Subjective Risk Level*
Target: Trust	Interaction Scenarios	
	Max Objective Risk	
	Max Cyclist Speed	
	Mean Distance to the Curb	
	Subjective Risk	

The model originally includes Max Objective Risk, Max Cyclist Speed, Mean Distance to the Curb and Subjective Risk as random parameters. The model shows statistically significant intercept for the Subjective Risk Level as a random parameter. However, the model fit analysis points that the model with a random intercept shows the best model fit (Akaike Corrected Criterion =115,354; Bayesian=139,3) and was chosen for further analysis.

Model Term	Coefficient ▼	Std.Error	t	Sig.	95% Confidence Interval	
					Lower	Upper
Intercept	3,520	0,459	7,662	,000	2,607	4,433
Gender=female	-0,215	0,251	-0,859	,392	-0,713	0,283
Gender=male	0,000ª					
RHS=curb	0,065	0,056	1,157	,250	-0,046	0,176
RHS=grass	0,000ª					
InteractionScenarios=automated following	0,628	0,118	5,307	,000	0,393	0,863
InteractionScenarios=automated overtaking	0,478	0,139	3,436	,001	0,202	0,755
InteractionScenarios=manual following	0,629	0,123	5,098	,000	0,384	0,874
InteractionScenarios=manual overtaking	0,536	0,141	3,797	,000	0,255	0,816
InteractionScenarios=no vehicle	0,000ª					
SubjectiveRiskLevel	-0,024	0,005	-4,672	,000	-0,035	-0,014
MaxObjectiveRisk	0,004	0,002	2,125	,036	0,000	0,007
MeanDistancetotheCurb	-0,792	0,356	-2,225	,029	-1,500	-0,085
MaxCyclistSpeed	0,131	0,054	2,414	,018	0,023	0,238

Figure 41: Fixed effects

Pairwise Contrasts

Interaction Scenarios Pairwise Contrasts	Contrast Estimate ▼	Std. Error	t	df	Adj. Sig.	95% Confidence Interval	
						Lower	Upper
automated following - automated overtaking	0,149	0,079	1,888	89	0,062	-0,008	0,307
automated following - manual following	-0,001	0,072	-0,020	89	0,984	-0,145	0,142
automated following - manual overtaking	0,092	0,089	1,036	89	0,303	-0,085	0,269
automated following - no vehicle	0,628	0,118	5,307	89	0,000	0,393	0,863
automated overtaking - automated following	-0,149	0,079	-1,888	89	0,062	-0,307	0,008
automated overtaking - manual following	-0,151	0,085	-1,782	89	0,078	-0,319	0,017
automated overtaking - manual overtaking	-0,057	0,076	-0,760	89	0,450	-0,208	0,093
automated overtaking - no vehicle	0,478	0,139	3,436	89	0,001	0,202	0,755
manual following - automated following	0,001	0,072	0,020	89	0,984	-0,142	0,145
manual following - automated overtaking	0,151	0,085	1,782	89	0,078	-0,017	0,319
manual following - manual overtaking	0,094	0,087	1,074	89	0,286	-0,079	0,267
manual following - no vehicle	0,629	0,123	5,098	89	0,000	0,384	0,874
manual overtaking - automated following	-0,092	0,089	-1,036	89	0,303	-0,269	0,085
manual overtaking - automated overtaking	0,057	0,076	0,760	89	0,450	-0,093	0,208
manual overtaking - manual following	-0,094	0,087	-1,074	89	0,286	-0,267	0,079
manual overtaking - no vehicle	0,536	0,141	3,797	89	0,000	0,255	0,816
no vehicle - automated following	-0,628	0,118	-5,307	89	0,000	-0,863	-0,393
no vehicle - automated overtaking	-0,478	0,139	-3,436	89	0,001	-0,755	-0,202
no vehicle - manual following	-0,629	0,123	-5,098	89	0,000	-0,874	-0,384
no vehicle - manual overtaking	-0,536	0,141	-3,797	89	0,000	-0,816	-0,255

Figure 42: Pairwise Contrasts

In comparison with the no vehicle interaction scenario the highest level of trust has automated following (p=0,000, magnitude=0,628) and manual following (p=0,000, magnitude=0,629). Manual overtaking has mean value of trust (p=0,000, magnitude=0,536) and automated overtaking have the lowest value of trust (p=0,001, magnitude=0,478). The pairwise comparison shows no statistically significant relationship between scenarios with vehicles. There is a statistically significant (p=0,000) relationship between Subjective Risk Level and Trust Level. With the increase of the trust on 1 unit the Subjective Risk Level decreases on 0,024. There is a statistically significant (p=0,036) relationship between max objective risk and trust level. With increase of trust level on 1 unit the max objective risk increases on 0,004.

The mean distance to the curb decreases with the increase of trust level (p=0,029). Two participants with the difference of trust in 1 unit will have difference in mean distance to the curb of 0,792 sm. Max cyclist speed increases on 0,131 with a 1 unit increase in trust level (p=0,018). The regression equation for this model has a following form:

$$S = 3{,}520 + 0{,}628x + 0{,}478y + 0{,}629z + 0{,}536g - 0{,}024h + 0{,}004k - 0{,}792m + 0{,}131n \pm 0{,}093$$

Where, 3,520 is a mean value of the Trust Level for the participant experiencing the subjective risk level of 0, max objective risk of 0, riding with the distance to the curb 0 cm and max cyclist speed 0 on the interaction scenario with no vehicle. In this model was fins statistically significant (p=0,05) variability within rides of same participant equals to the 0,093. According to this model the strongest individual predictor is a lateral mean distance to the curb.

Table 22: Variables of the regression equation of the GLMM for the trust

Variables	***Description***
X	1 if automated following, 0 if no vehicle
Y	1 if automated overtaking, 0 if no vehicle
Z	1 if manual following, 0 if no vehicle
G	1 if manual overtaking, 0 if no vehicle
H	Subjective Risk Level
K	Max Objective Risk
M	Mean Distance to the curb
N	Max Cyclist Speed

Residual Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Var(RideNumber=0)	0,164	0,088	1,876	,061	0,058	0,467
Var(RideNumber=1)	0,219	0,107	2,057	,040	0,085	0,568
Var(RideNumber=2)	0,083	0,045	1,842	,065	0,029	0,241
Var(RideNumber=3)	0,102	0,055	1,853	,064	0,035	0,294
Var(RideNumber=4)	0,036	0,025	1,456	,145	0,009	0,139
Var(RideNumber=5)	0,051	0,029	1,791	,073	0,017	0,153
Var(RideNumber=6)	0,055	0,030	1,833	,067	0,019	0,159
Var(RideNumber=7)	0,123	0,063	1,965	,049	0,045	0,333
Var(RideNumber=8)	0,012	0,013	0,924	,355	0,001	0,101
Var(RideNumber=)	0,093	0,047	1,956	,050	0,034	0,253

Covariance Structure:Diagonal
Subject Specification:ParticipantNumber
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Figure 43: Variability within rides

5.6.4 The Generalized Linear Mixed Model for the trust in overtaking scenarios

Table 23: Input parameters to the GLMM for the trust in overtaking scenarios

	Fixed Effects	***Random Effects***
Subject: Participants number	Gender	Random intercept
Repeated measures: Rides number	RHS	
Target: Trust	Interaction Scenarios	
	Max Objective Risk	
	Max Cyclist Speed	
	Mean Distance to the Curb	
	Subjective Risk	
	Overtaking Speed	
	Overtaking Distance	

The model shows the relation between Trust Level for overtaking and independent parameters. As random parameters, model originally include: Max Objective Risk, Max Cyclist Speed, Mean Distance to the Curb, Subjective Risk, Overtaking Speed and Overtaking Distance. None of the random effects shows statistically significant influence. The model with the random intercept with the fit of Akaike Corrected Criterion =80,705; Bayesian=84,316 was chosen for further analysis.

Model Term	Coefficient ▼	Std.Error	t	Sig.	95% Confidence Interval	
					Lower	Upper
Intercept	5,099	1,133	4,499	,000	2,784	7,413
Gender=female	-0,092	0,212	-0,434	,667	-0,525	0,341
Gender=male	0,000[a]					
InteractionScenarios=automated overtaking	0,073	0,095	0,769	,448	-0,121	0,268
InteractionScenarios=manual overtaking	0,000[a]					
RHS=curb	0,041	0,102	0,402	,691	-0,167	0,249
RHS=grass	0,000[a]					
SubjectiveRiskLevel	-0,046	0,012	-3,703	,001	-0,071	-0,021
MaxObjectiveRisk	0,005	0,003	1,687	,102	-0,001	0,010
MeanDistancetotheCurb	-0,996	0,701	-1,420	,166	-2,428	0,437
MaxCyclistSpeed	-0,042	0,144	-0,290	,773	-0,336	0,252
OvertakingSpeed=5	0,102	0,102	1,000	,325	-0,106	0,310
OvertakingSpeed=10	0,000[a]					
OvertakingDistance=1	0,118	0,102	1,159	,256	-0,090	0,326
OvertakingDistance=3	0,000[a]					

Probability distribution:Normal
Link function:Identity

[a]This coefficient is set to zero because it is redundant.

Figure 44: Fixed effects

There is a statistically significant (p=0,001) negative relationship between Subjective Risk Level and Trust Level. With the increase of the Subjective Risk on 1 unit the Trust Level decreases on 0,046. The regression equation for this model is as follows: S=5,099 – 0,046x.

Where 5,099 is a mean value of the Trust level for the overtaking scenarios when participant have Subjective Risk level equal to 0, and X is a Subjective Risk Level.

5.6.5 The Generalized Linear Mixed Model for the objective risk

Table 24: Input parameters to the GLMM for the objective risk

	Fixed Effects	***Random Effects***
Subject: Participants number	Gender	Random intercept
Repeated measures: Rides number	RHS	
Target: Objective Risk Level	Interaction Scenarios	
	Cyclist Speed	
	Distance to the Curb	
	Relative Speed	
	Relative Distance	

As the model describing the Objective Risk relation with independent parameters was used model with the random intercept (Akaike Corrected = 14,433, Bayesian = 15,512). Originally was tested following random parameters: cyclist speed, distance to the curb, relative speed, relative distance, but none of them could reach statistically significant level.

Model Term	Coefficient ▼	Std.Error	t	Sig.	95% Confidence Interval	
					Lower	Upper
Intercept	10,085	1,721	5,861	,000	6,710	13,459
Gender=female	-0,496	1,375	-0,360	,719	-3,193	2,201
Gender=male	0[a]					
InteractionScenario=Automated Following	-4,550	0,516	-8,816	,000	-5,562	-3,538
InteractionScenario=Automated Overtaking	0,636	0,300	2,119	,034	0,047	1,225
InteractionScenario=Manual Following	-4,870	0,526	-9,252	,000	-5,903	-3,838
InteractionScenario=Manual Overtaking	0[a]					
RHS=Curb	-1,000	0,194	-5,146	,000	-1,381	-0,619
RHS=Grass	0[a]					
DistancetotheCurb	-0,353	0,856	-0,413	,680	-2,031	1,325
CyclistSpeed	-0,486	0,199	-2,435	,015	-0,877	-0,095
RelativeDistance	-0,426	0,033	-13,026	,000	-0,490	-0,361
RelativeSpeed	0,112	0,237	0,472	,637	-0,353	0,577

Probability distribution:Normal
Link function:Identity

[a]This coefficient is set to zero because it is redundant.

Figure 45: Fixed effects

Pairwise Contrasts

Interaction Scenario Pairwise Contrasts	Contrast Estimate ▼	Std. Error	t	df	Adj. Sig.	95% Confidence Interval	
						Lower	Upper
Automated Following - Automated Overtaking	-5,187	0,438	-11,855	1 988	0,000	-6,045	-4,329
Automated Following - Manual Following	0,320	0,218	1,468	1 988	0,142	-0,108	0,748
Automated Following - Manual Overtaking	-4,550	0,516	-8,816	1 988	0,000	-5,562	-3,538
Automated Overtaking - Automated Following	5,187	0,438	11,855	1 988	0,000	4,329	6,045
Automated Overtaking - Manual Following	5,507	0,457	12,043	1 988	0,000	4,610	6,404
Automated Overtaking - Manual Overtaking	0,636	0,300	2,119	1 988	0,034	0,047	1,225
Manual Following - Automated Following	-0,320	0,218	-1,468	1 988	0,142	-0,748	0,108
Manual Following - Automated Overtaking	-5,507	0,457	-12,043	1 988	0,000	-6,404	-4,610
Manual Following - Manual Overtaking	-4,870	0,526	-9,252	1 988	0,000	-5,903	-3,838
Manual Overtaking - Automated Following	4,550	0,516	8,816	1 988	0,000	3,538	5,562
Manual Overtaking - Automated Overtaking	-0,636	0,300	-2,119	1 988	0,034	-1,225	-0,047
Manual Overtaking - Manual Following	4,870	0,526	9,252	1 988	0,000	3,838	5,903

Significant contrasts are shaded gold. The least significant difference adjusted significance level is .05.

Figure 46: Pairwise Contrasts

There is a statistically significant (p=0,000) relationship between Trust Level and the Subjective Risk Level with a magnitude of -6,690. With the improvement trust on 1 unit the predicted Subjective Risk will be reduced on -6,690. If there are two participants with the difference in Subjective Risk level of 1 unit their trust level will be different on 6,690.

Also, there is a statistically significant (p=0,000) relationship between Right hand side object and Objective Risk. The curb side have 1 Joule Objective Risk less than the Green Grass side.

Another statistically significant (p=0,015) relationship is found between Objective Risk and the Cyclist Speed. With the increase of Cyclist Speed on 1 m/s the Objective Risk declines on the 0,486 Joules. It can be explained by the change in the relative distance, probably with the increase of speed the vehicle driver tends to keep bigger distance between cyclist and car.

The relationship between Relative Distance and the Objective Risk is also statistically significant (p=0,000). With the increase of the distance between objects on 1 m, the Objective Risk reduces on 0,426 Joules. The same as if we compare 2 participants with the difference in related speed of 1 m the Objective Risk will be different on 0,426 Joules.

A statistically significant (p=0,000; p=0,034; p=0,000) relationship exist between Interaction Scenarios and Objective Risk Level. The Automated Following scenario comparing to the Manual Overtaking Scenario have lower Objective Risk on 4,550 Joules. Also, Manual Following have 4,870 Joules less of Objective Risk comparing to the Manual Overtaking. While, the Automated Overtaking scenario have 0,636 Joules more than Manual Overtaking. Overall, the lowest Objective Risk in comparison with the Manual Overtaking have the Manual Following, while Automated Following have slightly higher risk level and the highest risk level out of all interaction scenarios have the Automated Overtaking. The pairwise comparison shows that the Automated Overtaking have higher Objective Risk than Automated Following on 5,187 Joules (p=0,000). The Automated Overtaking have higher Objective Risk than Manual Following on 5,507 (p=0,000).

The regression equation for this model is as follows: $S = 10{,}085 – 4{,}550x + 0{,}636y – 4{,}870z - 1h – 0{,}486g – 0{,}426k$

Where, 10,085 Joules of Objective Risk corresponds to the mean value of the Objective Risk for the participant experiencing the interaction with manually overtaking vehicle on the side of the road with green grass and cycling with a speed of 0 m/s and relative distance of 0 m. For this model the strongest individual predictor is the interaction scenario with a manually following vehicle.

Table 25: Variables of the regression equation of the GLMM for the objective risk

Variables	***Description***
X	1 if automated following or 0 if no vehicle
Y	1 if automated overtaking or 0 if no vehicle
Z	1 if manual following and 0 if no vehicle
H	1 if curb side or 0 if grass side
G	Cyclist Speed
K	Relative Distance

5.7 Graphical analysis of parameter changes along the route

All dynamic graphs are shown in the appendix. This section discussed only graphs with significant interaction effect between variables. The X axis of all graphs represents the % of the completion of the route, recalculated from the travelling time that each participant took to complete the route. Therefore, 100% stands for the time that participant spent to finish a route and 0% stands for the first second of travelling.

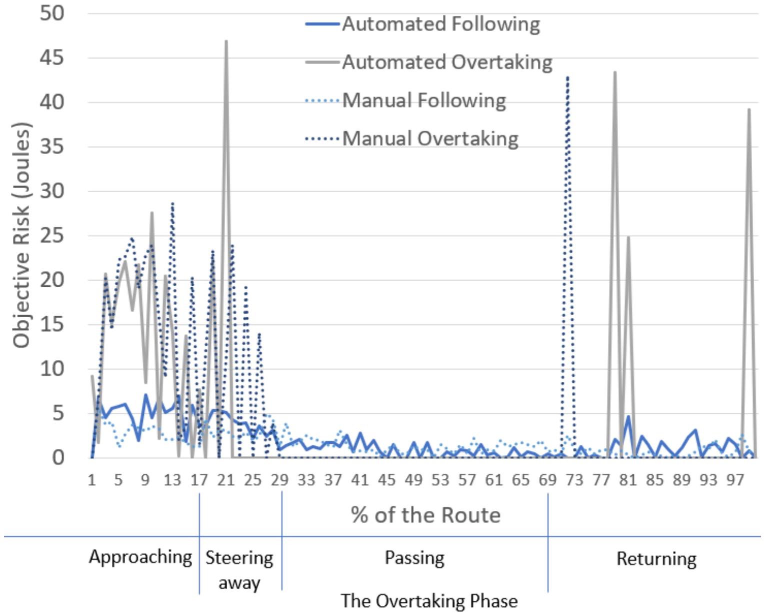


Figure 47: The Objective Risk along the route

The Figure 47: The Objective Risk along the route Figure 47 shows that overtaking maneuvers have higher values of objective risk than the following maneuver. However, the duration of the interaction time is higher in the case of the following maneuvers. Both interaction scenarios have higher values at the beginning of the route, when participants are getting used to the bicycle and did not yet stabilized their movement. The overtaking maneuvers have Objective Risk bursts at the phase of approaching to overtake and coming back to the lane. The minimal value part of the overtaking maneuver refers to the reduced probability of collision, given that objects moving parallel to each other have a low probability of collision. Automated and Manual driving modes have the same levels of objective risk for both vehicle maneuvers.

The Figure 48 shows the change of the Distance to the Curb according to the part of the Overtaking maneuver. Cyclists start cycling closer to the curb when the vehicle goes parallel to the cyclist and come back to the original distance after the vehicle returns to the lane in front of cyclist. The Distance to the Curb have slightly lower values for the Automated driving mode than for the Manual driving mode.

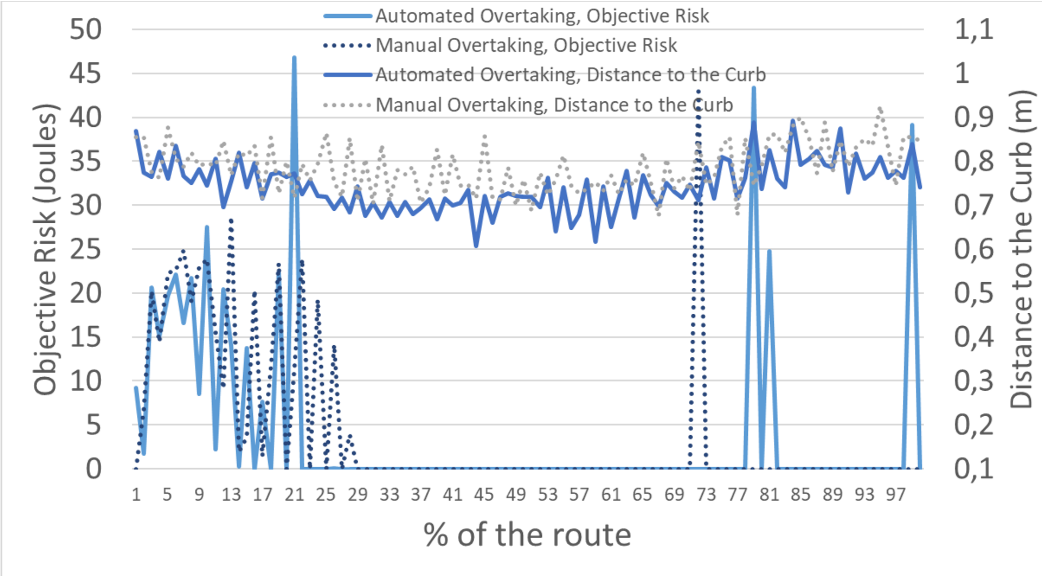


Figure 48: The Objective Risk and the Distance to the Curb along the route

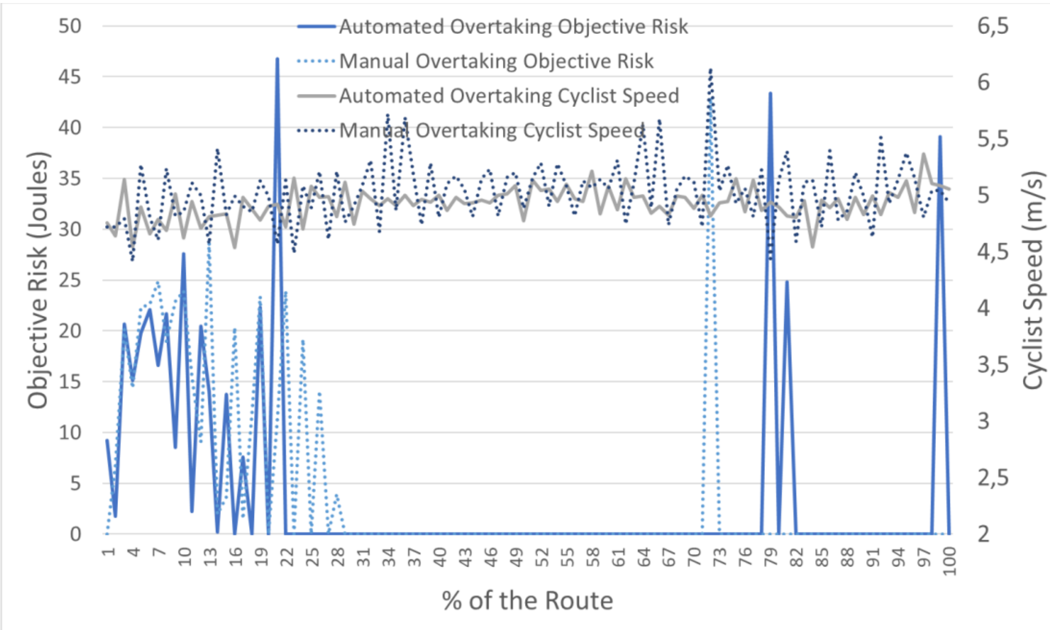


Figure 49: The Objective Risk and the Cyclist Speed along the route

The Figure 49 presents the cyclist speed and Objective risk along the route. We can observe that the cyclist speed increases slightly when the vehicle overtakes it. At the same time, the speed has higher values for the manual overtaking scenarios in comparison to the automated overtaking scenarios.

The Figure 50 above shows interaction between the Objective Risk (blue line) and the Relative Distance (grey line). The following maneuver graphs show a clear relation between decrease of Relative Distance between the vehicle and the cyclist and the increase in Objective Risk. The overtaking maneuver graphs also shows relation between Distance to the Curb and Objective Risk. However, in the case of Overtaking maneuvers the Objective Risk also influenced by the other attributes.

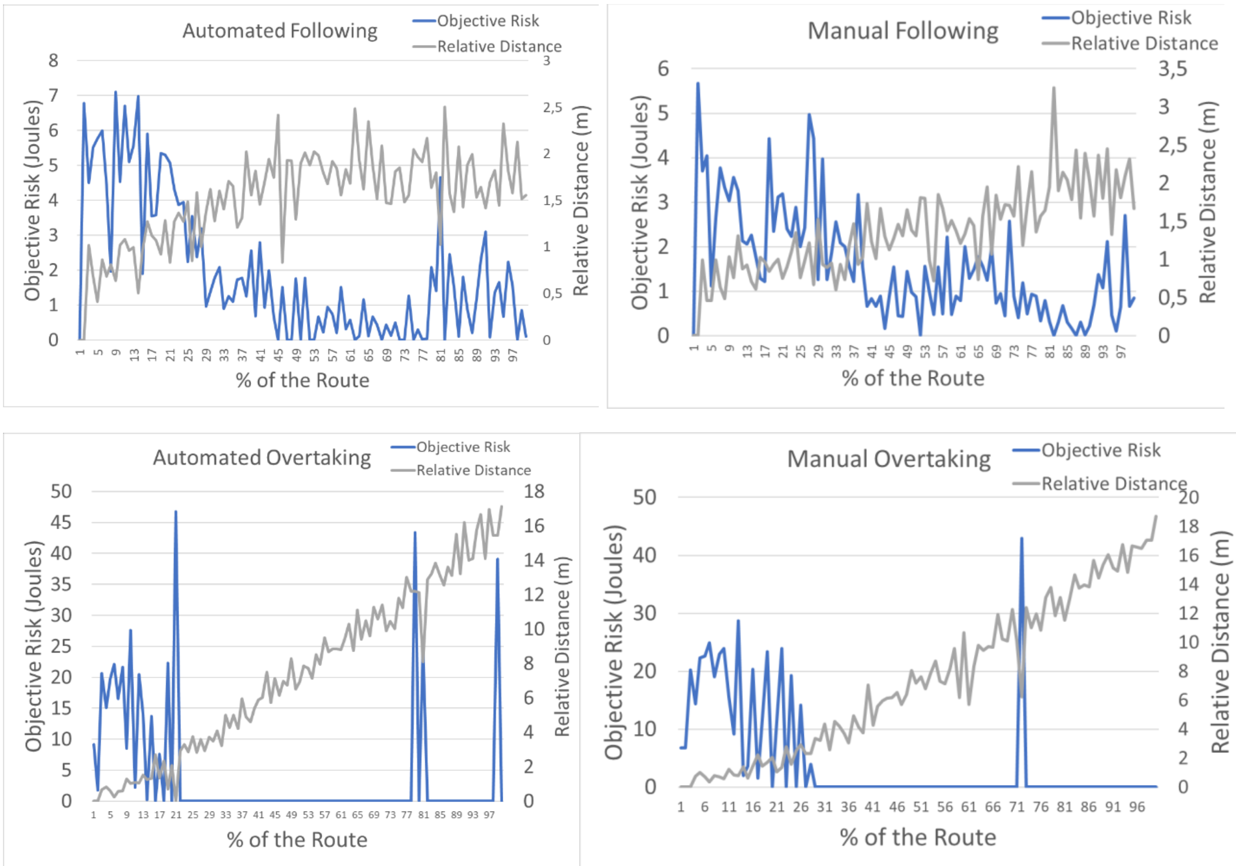


Figure 50: The Objective Risk and the Relative Distance along the route

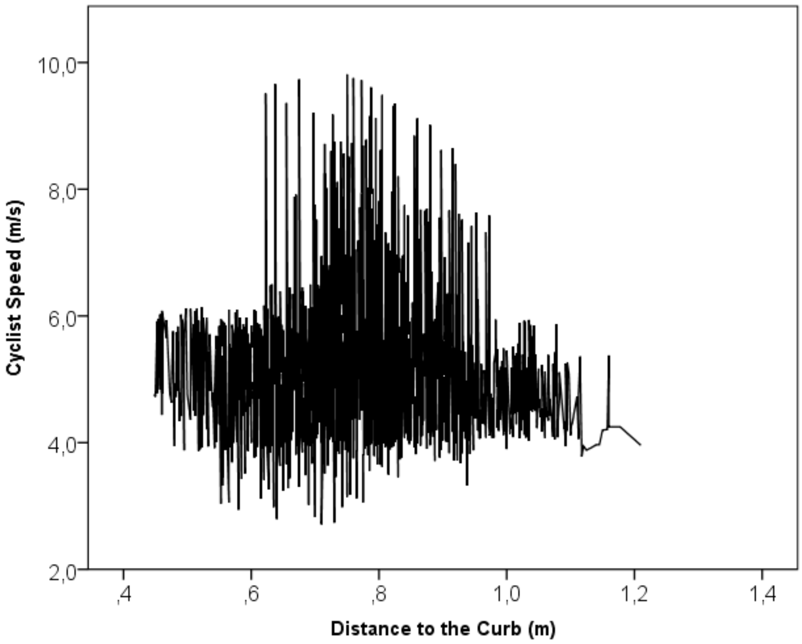


Figure 51: Dependence of the Cyclist Speed on the Distance to the Curb

The Figure 51 of the cyclist speed and the distance to the curb along the route shows that cyclists reach the highest speed in the middle part of the lane. When the cyclist goes closer to the curb or closer to the vehicle lane the speed drops. For some cyclists the speed reduction for the lane part closer to the curb is even larger than the speed reduction for the parts closer to the vehicle lane.

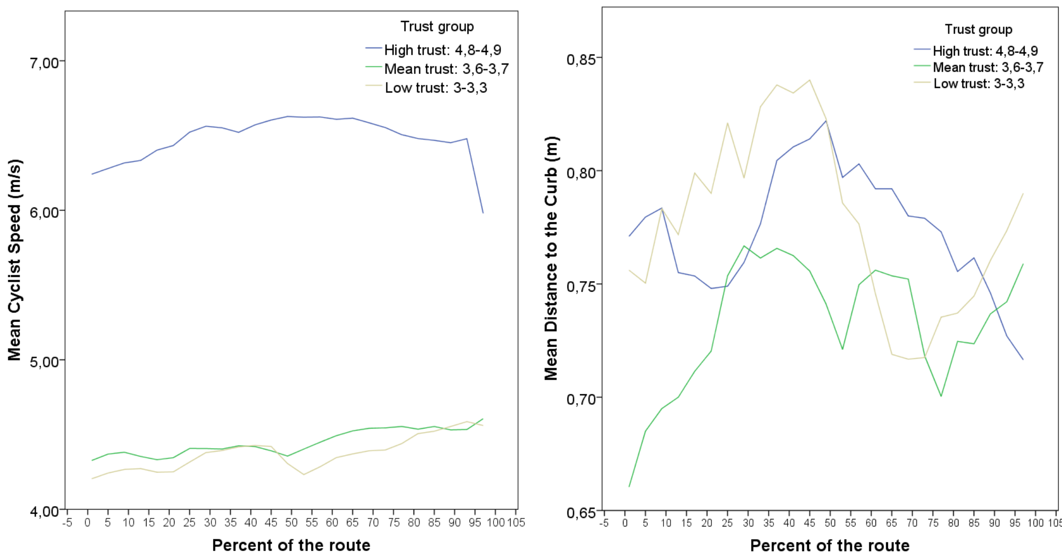


Figure 52: For different trust groups, the cyclist speed and distance to the curb along the route

Looking on the Figure 52 showing the change of the cyclist speed and the distance to the curb with a time of the experiment, we can observe that the speed level has a slight change with time, while the position of the cyclist on a bicycle lane (represented by the distance to the curb) varies significantly.

To check how the trust level influences the behavior of cyclist, three groups of people were defined: low level of trust, corresponding to trust level from 3 to 3,3; mean level of trust, corresponding to trust level from 3,6 to 3,7; and high level of trust, corresponding to trust level from 4,8 to 4,9. The higher trust group has higher cycling speed during the whole time of the experiment and keeps their position on the lane more coherent. These two characteristics are be interrelated, as to keep a high speed a certain balance have to be reached and with variation of the position on a lane the balance can be lost. The mean trust group and low trust group have a similar speed range. However, the low trust group have a big variation in its position on the lane. The people with low trust level tends to vary their position more often and with bigger amplitude.

5.8 Observation studies

Participants show similarity in the behavioral pattern. In the following scenario appear a moment when participant start looking back to check the vehicle behavior. The Figure 53 shows the moment when participants start being worrying of vehicle behavior as then the distance from the cyclist to the curb reduces.

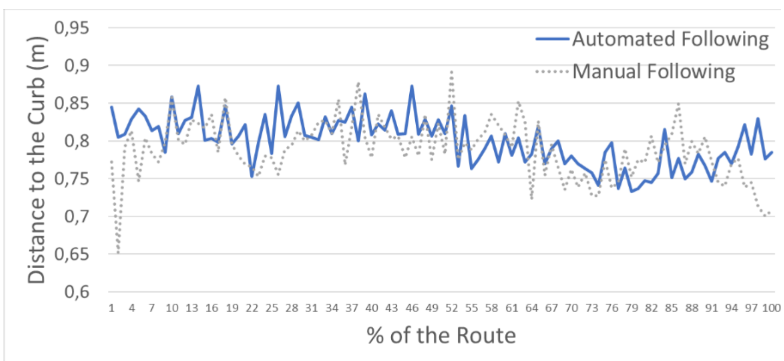


Figure 53: The Distance to the Curb along the route

5.9 Discussion and summary

This chapter conducted analysis and obtained results on trust, subjective and objective risks and attributes of interaction scenarios. The summary of results is presented in the Table 26. This section discusses similarities and differences in the master thesis research findings and reviewed literature findings, shown in the chapter 2. There was a research gap on the studies about the behavior of cyclist in interaction with automated vehicle and in the risk perceived by cyclist in the interaction scenarios. Some of the results obtained are unexpected, for example, related to changes in behavior in risky interactions and to the perception of risk in interaction with attributes. Possible reasons for these findings are discussed in this section.

Table 26: Summary of results

	Subjective Risk	***Trust***	***Objective Risk***
Statistical Analysis Boxplot, Wilcoxon test, T-test	Following < Overtaking 3,5 < 1,5		Following < Overtaking
Correlation Analysis - Negative correlation + Positive correlation	-Trust -Overtaking speed* * After Bonferroni correction the null hypothesis can not be rejected	-Subjective Risk +Objective Risk - Max distance to the curb	+Trust -Distance to curb -Relative distance -Relative speed Relative distance + Relative speed Relative speed – Distance to the curb Distance to the curb – Relative distance
Generalized Linear Mixed Model AF – automated following AO – automated overtaking MF – manual following MO – manual overtaking	-Trust Curb < Grass AF > no vehicle AO > no vehicle MF<AO 3,5 < 1,5	-Subjective Risk +Objective Risk - Mean Distance to the Curb + Max Cyclist Speed + Learning with a time of experiment	AF<MO<AO MF<MO<AO Curb<Grass -Relative distance -Cyclist speed
Graphical Analysis	Cyclist Speed highest in the middle distance from curb Cyclist Speed higher for people with high trust	Distance to Curb: less in following < overtaking Distance to curb: manual < automated Distance to Curb values vary less for higher trust Mean distance to curb in 1,5< in 3,5	Interaction time less for Overtaking < Following
Statistical Analysis for Following with 3 m and Overtaking with 3,5 m.	Same	Same	Following < Overtaking
Statistical Analysis of the RHS objects	Curb<Grass Distance to curb: grass<curb Cyclist speed: grass>curb Relative distance: grass> curb	Grass<Curb	Grass>Curb

Research regarding cyclist and AV interaction are limited, since most of the literature focuses on the interactions of pedestrians and AVs. Rodriguez Palmeiro et al. (2017), Böckle et al., (2017); Habibovic et al., (2018); Merat et al., (2017) and Hagenzieker et al. (2018) show that pedestrians generally feel less safe and behave more cautiously when interacting with AVs. The master thesis research found that participants feel less safe, increase their speed and reduce the distance to the curb during overtaking by AVs. However, for the following maneuvers there is no difference in behavior and perception between automated and manual driving.

With respect to overtaking attributes, the literature shows that, from the side of the vehicle drivers, an increase in overtaking lateral distance leads to an increase in speed. Furthermore, at a speed of 45 km/h vehicle drivers choose to overtake with 1,5 m distance and may sometimes overtake with a distance of 1 m (Debnath et al., 2018; Parkin & Meyers, 2010; Parkin & Schackel, 2014). The master thesis shows that for the cyclist the increase in distance and increase in speed are always preferred. The mean speed of cyclist was equal to 14 km/h - 15,5 km/h, which means that the vehicle was overtaking with the speed of 19 km/h - 25,5 km/h. In all cases, participants prefer an overtaking distance of 3,5 m rather than 1,5 m.

Dozza, Schindler, Bianchi-Piccinini, & Karlsson, (2016); Dufour, (2010) mentioned that the mean distance from the curb for cyclists is equal to 0,25 or 0,3m to the small curb or 0,6m to the big curb. The master thesis research shows similar results as the mean distance that cyclists keep from the curb in the scenarios with vehicles is equal to 0,76-0,81m, while in scenarios without the vehicles the mean distance is 0,81m. This value corresponds to the middle of the standard bicycle lane (of 1,5 m width). In the passing part of the overtaking maneuver, the distance to the curb is reduced to 0,6-0,7 m.

Research of Chuang, Hsu, Lai, Doong, & Jeng, (2013); Walker, (2007) shows that the vehicle drivers keep more distance while overtaking female cyclists than male cyclists. The research of Yannis et al., (2013) reported that the gender of participants influence on their trust to interaction with AVs. Both conclusions correspond to the findings of the master thesis research, as analysis shows that female participants experience lower trust and higher subjective risk and tend to go closer to the curb to keep larger lateral distance with the overtaking vehicle.

Chuang et al. (2013) claims that longer passing time influences the observed increase in speed of cyclist. This study fully confirms this finding, showing that the speed of the cyclist increases during overtaking and that the cyclist prefers to be overtaken with a higher speed in order to reduce the interaction time.

Research on the trust to automated vehicle technologies reports that under-trust may be cause of the accidents with the system Hoff & Bashir, (2015). The master thesis research did not capture any participant with under-trust. However, participants with reduced trust demonstrated changed and unsafe behavior, varying frequently their position on the lane and causing loss of balance. The danger of the opposite concept of over-trust to the system was mentioned by Lee & See, (2004). Lee & See, (2004) also mentioned that people tend to over-trust the novel automated vehicle system. Indeed, the master thesis research was able to capture some participants with a high level of trust and these participants cycled with a much higher speed than the others. However, the correlation between trust level and cycling experience is still not fully understood.

Mayer (1995), Lee & See (2004) and Korber (2019) proposed the following questionnaire sections to capture the change in trust levels: trust in automation, propensity to trust, intention of developers, understandability and reliability. The research recognizes an influence of “understandability” and “trust in automation” in the attitude of participants, which was not the case for “intentions of developers”. “Propensity to trust” and “reliability” were corresponding and had the same pattern of changes.

With respect to factors influencing trust level of participants, researchers reported that the most influencing factors are speed of the vehicle and distance to the AV (Oxley et al., 2005; Rodríguez Palmeiro et al., 2018; Yannis et al., 2013). The master thesis research obtained the same results. However, the second most influencing factor on participants after the relative distance factor was the vehicle characteristics, which stands for the size of the vehicle and the noise of the vehicle. This finding is in line with results from Yannis et al., (2013) and Weddell (2012) who mentioned the size of the automated vehicle as an influecing factor. Rodríguez Palmeiro et al. (2018) and Lagstrom & Lundgren (2015) found that pedestrians decisions not to cross in front of AV was influenced by the driver inattentiveness. In the master thesis research, participants did not pay significant attention to the driver behavior. The research from Rodríguez Palmeiro (2018) and Lagstrom (2015) focused on interaction of pedestrians with AV, while in the thesis research AV interacts with cyclist. Since cyclists concentrated on keeping balance and were barely able to see the car driver, they do not pay much importance to the eye contact with the driver. Besides all mentioned above parameters, Lagstrom & Lundgren, (2015) found that weather conditions can affect the interaction process, which was also observed in the master thesis research. Participants show the biggest trust and lowest subjective risk in day 2 with the temperature of +20 in comparison to day 1 with +30 and day 3 with +18.

The study covers a research gap on the behavior of cyclist in interaction with automated vehicle and the subjective risk appearing in interaction. Below discussed the unexpected findings and possible reasons for these results.

The research shows that the objective risk increases with the reduction of the distance to the curb. As distance to the curb is a parameter included in the probability part of the static risk field, the negative correlation between distance to the curb and objective risk in the following scenarios is expected. In the passing phase of the overtaking scenarios, the overtaking lateral distance and distance to the curb are interrelated, which means that when the distance to the curb reduces the lateral distance to the vehicle increases. This could help to reduce the Objective risk, resulting from the superposition of kinetic and static fields. However, reduced distance to the curb result in the increase in probability of the static risk field. On the other hand, increased distance to the vehicle does not result in the lower kinetic risk, as probability of collision in kinetic field is influenced by the crossing of polygons. Also, in the passing stage vehicle's and cyclist's polygons are not crossing. Thus, in the passing stage the main risk comes from the static object and decrease in the distance to curb increases the objective risk. Following that, the changes in cyclist behavior in risky situation, increase in speed and decrease in the distance to the curb results into the less safe interaction.

One of the most common reason for the accidents is speeding. In order to keep the interaction safe, all interacting objects should maintain the speed low. Participants were expected to follow the low speed logic. However, the subjective risk analysis shows unexpected results: cyclists prefer to be overtaken with the higher vehicle speed (in the research were assessed speeds below 40 km/h) and cyclists increase their speed in the passing phase of the overtaking. The negative correlation between subjective risk and overtaking vehicle speed can be explained by the interaction time reduction with increasing of the speed of the vehicle. The positive correlation between cyclist speed and subjective risk can be explained by the balance required for more stable cycling. Cyclists slightly increase speed to be more dynamically stable.

Another unexpected result is related to the right-hand side objects analysis. Cycling was assumed to be less risky near the green grass than near the asphalt pass. However, both subjective and objective risks increase when cycling on the green grass side in comparison with cycling on the asphalt path. Objective risk increases as cyclist starts cycling faster and closer to the curb, influenced by the increase in Subjective risk. The higher trust of the participants for the asphalt side can be explained by the fact that the curb is not high so participants may visually feel that the road is wider on the asphalt side and also perceive that they can always continue cycling on the pedestrian path, while cycling on the green grass is more difficult.

As one of the explanatory attributes, the relative speed was examined. However, this parameter did not provide a significant explanation for the level of risks changes. The vehicle driver was concentrated on keeping a certain relative distance and used the speed of the vehicle to adjust distance. As soon as the longitudinal relative distance reached the pre-defined value there is no need for the car to accelerate, therefore the relative speed is low when the relative distance is low. Thus, the analysis shows a negative correlation between objective risk and relative speed.

6 Conclusion and recommendations

The operation of automated vehicles in shared areas requires attention with respect to the interaction between AVs and vulnerable road users. There is a clear scientific gap on cyclist perception when interacting with automated vehicles. Currently, the programmed interaction behavior of AVs is based on the knowledge of the interaction between conventional vehicles and cyclists. However, cyclists may react differently to conventional and automated vehicles.

This research is part of the I-AT project of the Royal Haskoning DHV. The I-AT project aims to design a public transport line using automated shuttle buses. The Automated Shuttle Bus (ASB) programmed behavior requires the shuttle bus to follow detected leading object in the automated driving mode or overtake the object in manual driving mode. Following maneuvers may have negative impact on the safety of the traffic situation and it is not clear which level of Subjective and Objective Risks are experienced by the cyclists in this context.

This research investigates the potential interaction scenarios between automated vehicle and cyclists to evaluate the subjective and objective risk resulting in each interaction scenario and interaction attributes. The thesis methodology is based on a field-experiment. Cyclist perceptions of the interaction process were assessed with respect to subjective risk and trust. Objective Risk was assessed using the Probabilistic Driving Risk Field (PDRF) safety method.

This chapter discusses the main findings of the study, answers the research questions, discusses the main practical contributions for the I-AT project, points out the limitations of the research and gives recommendations for future research.

6.1 Key findings

To answer the main research question, firstly the research sub-questions are answered as following:

SQ 1: Which interaction scenarios are possible when an automated vehicle approaches a cyclist from behind?

In general, the interaction scenarios between cyclists and automated vehicles can be divided into two groups: scenarios when the vehicle is approaching cyclist from behind and crossing interaction scenarios. Crossing interaction scenario refers to the case when the trajectories of a cyclist and a vehicle cross each other. In this situation, cyclists have to make a decision whether to let the vehicle pass first or cross first. Approaching from behind interaction scenarios refer to the situation when a cyclist and a vehicle are moving in the same direction. In case the automated vehicle is approaching the cyclist from behind, two sub-scenarios emerge, the first is following, i.e. when the automated vehicle approaches the cyclist from behind and moves with the cyclist speed, the second is overtaking, i.e. when the automated vehicle passes the cyclist. As this research is part of the I-AT project, which aims to design a public transport line serviced by an automated shuttle, in this study we focus only on the passing interaction scenarios, which are more relevant for the I-AT. In addition, we focus only on scenarios where the vehicle and the cyclist operate on shared areas, as these scenarios have higher risk levels. The literature review reveals a gap in the knowledge about cyclist reaction on the maneuvers of the automated vehicle.

To consider cyclist reactions on each operation mode, this research includes four scenarios: automated following, automated overtaking, manual following and manual overtaking.

SQ 2: What is the cyclist subjective risk level for each of the interaction scenarios?

Perceived risk was assessed using self-reported subjective risk, trust and cyclist behavior. All three measures are interrelated. Subjective Risk and Trust are negatively correlated. Cyclist behavior, represented by cyclist speed and cyclist distance to the curb, changes for different levels of Trust and Subjective Risk.

Self-reported subjective risk is higher for overtaking scenarios than for following scenarios. There is no statistically significant difference in subjective risks for driving in automated mode or in manual mode. However, Subjective Risk is negatively correlated with overtaking lateral distance.

The pattern of **cyclist behavior** in the situation of high subjective risk was captured based on the behavior of cyclist in the passing phase of the overtaking scenarios. The cyclist increases the cycling speed and decreases the distance to the curb when the risk level rises. For the automated driving the distance to the curb is reduced in comparison to the manual driving.

There is no evidence of significant change of **trust** in between interaction scenarios. As participants feel extremely vulnerable in interactions with vehicle, they do not differentiate between the levels inside the dangerous zone. This is supported by the fact that participants mentioned the vehicle characteristics, size and noise, as the second most influencing factor, which means that participants already feel unsafe in operation with vehicle itself. For all interaction scenarios, participants with a higher rate of confidence have higher cycling speed and keep distance to the curb more consistent.

One of the aims of the research was to assess the relation between the perceived risk and objective risk. The self-reported subjective risk does not have significant correlation with the Objective Risk. The discrete nature of the self-reported subjective risk value makes it difficult to predict with which moment of the ride participants associate the reported risk level. Trust has a positive correlation with the Objective Risk values, as increased speed of the cyclist with a high trust level increases the Objective Risk. The behavioral subjective risk is highest during the passing phase (as at this phase cyclist goes closer to the curb) while the Objective Risk has the highest values during the steering away phase and the returning phase. Following that, it can be concluded that there is a certain mismatch between perceived risk and objective risk.

SQ 3: What is the objective risk level for the interaction scenarios?

The objective risk level is a continuous measure, calculated for every 0,2 seconds of rides with the Probabilistic Driving Risk Field safety algorithm. The overtaking maneuvers have higher objective risk than following maneuvers. In following maneuvers, no significant relation was found between the level of objective risk and the vehicle driving mode (automated/manual). In overtaking, the highest values of Objective Risk participants experienced during the automated driving. Overall, in overtaking maneuvers, Objective Risk has the highest risk values during the steering away phase and the returning phase, while in the stage of passing the Objective Risk is low due to the low probability of the accident in the Kinetic Field. On the level of objective risk has influence two attributes: the objective risk has negative correlation with the distance to the curb, and negative correlation with the relative distance. The objective risk also has negative correlation with the cyclist speed, as there is a positive correlation between the speed of cyclist and the relative distance.

SQ 4: What are possible solutions to lower subjective and objective risks levels in the interaction scenarios?

In the experiment two driving modes were tested, however the attributes have the same influence for driving in manual and automated mode. The research found three main influencing attributes on the risk levels.

The relative distance between objects has negative correlation with the Objective and Subjective Risks. In the scenarios where following and overtaking had same relative distance the Subjective Risk and trust had same values for both interaction scenarios.

Another influencing attribute is a **time of interaction**, to maintain safe interaction the time of interaction have to be reduced. The Subjective Risk declines when the overtaking speed increases and the interaction time decreases. However, there was no statically significant relationship between vehicle overtaking speed and Subjective Risk after applying the Bonferroni correction. The behavior of cyclist also shows the need of reduction of the interaction time. In the end of ride in the following scenarios, cyclist increase their speed or participants start looking behind to watch the following vehicle which result in loss of balance. In the overtaking scenarios, cyclists have a higher speed and cycling closer to the curb during the passing maneuver, which can result in the loss of balance and accident. Thus, a reduction in the time of the passing phase required to reduce the time of dangerous behavior.

The right-hand side objects also have influence on the risk of interactions. For the interaction scenarios with the grass beside the road the subjective and objective risks levels are higher and trust levels are lower than on the asphalt beside the road. Analysis of parameters also approves this influence, as on the grass side of the road the variation in the participant position on the road is larger, the distance to the curb is smaller, and cyclist speed is higher. Originally, it was assumed that the grass side of the road is less risky than the asphalt side of the road, and the parameter of the rigidity of the road boundary object of the PDRF static field for the green grass has less value than the one for the asphalt side. However, the Objective Risk for the green grass side of the road is higher than the Objective Risk for the asphalt side.

Answers on the sub-questions allow to give a recommendation for the general research question: *Which interaction scenarios minimize Subjective and Objective Risks appearing when an automated vehicle approaches a cyclist from behind?*

There is a clear evidence that the overtaking maneuver has a higher risk level than the following maneuver. However, the time of the interaction has high impact on the cyclist behavior and in the overtaking scenario the interaction time is much lower. Thus, it can be concluded that for short distances the following approaches are a safe option. Besides exact vehicle maneuver, also mode of operations has an influence on the risk levels. For the following scenario there is no clear difference between modes. Following in automated mode has the same level of risk as following in manual mode. For the overtaking scenarios, the automated mode has clearly higher risk level than the manual driving. The choice of the operation scenario is influenced by the available relative distance. The higher the distance the lower the risk. For the wide street of 3 meters the overtaking scenarios have same subjective risk as the following option. Besides overtaking with a higher distance another recommendation could be to reduce the interaction time by overtaking with a high speed, (in the research were assessed speeds below 40 km/h). Information about the right-hand side objects should be considered for deciding over the vehicle operation parameter. The streets with the green grass on their sides are perceived by cyclist as more dangerous.

6.2 Contribution for the I-AT project

This research aims to increase the safety of operation of the I-AT project Automated Shuttle Bus by increasing awareness on the interaction processes with cyclists. It also aims to explore the possibility of increasing vehicle operation time in the automated mode. As a result of the research, three safety approaches are recommended to the I-AT project.

The direct outcome of this research can be used for training ASB drivers, by increasing their awareness regarding the interaction process with cyclists. The driver's manual document and trainings should explain the correlation between distance of overtaking and speed of overtaking to the Subjective and Objective Risks and point out the importance of the different interaction scenarios for different surrounding infrastructure, for example in the case of the influence of right-hand side objects in cyclist's behavior. The driver's manual can recommend the driver in which interaction situations the vehicle mode has to be switched to manual and when the Automated Shuttle Bus can safely operate in automated driving mode.

To provide an even more precise idea to the driver about the safety of interaction, a digital screen can be built which shows in real time the value of the Objective and Subjective Risks and give recommendation on the preferred behavior. In that case the Objective Risk can be assessed using the PDRF safety algorithm; the k values can be chosen based on the findings of this research; and the Subjective Risk can be built up from the Trust and Subjective Risk equations of the Generalized Linear Mixed Model GLMM.

Another safety approach relates to the route assessment protocol. The optimal behavior of the vehicle in each part of the route can be assessed upfront using the GLMM regression equations. The current approach of the I-AT project calculates the needed ASB operation conditions based on the safety of each object in interaction separately, not taking into account the change of behavior due to interaction between objects. The ASB safety approach is based on the required lateral clearance for object to operate with a certain speed, and distance that the vehicle will cover in case of system break before the human driver takes the vehicle control. Thus, the approach that the ASB follows now is to reduce speed with the reduction of the available relative distance (Bangarraju, Ravishankar, & Mathew, 2016; I-AT, 2019). This is a sufficient approach for keeping the high safety level of the vehicle itself, as evidenced by the master thesis research finding that the cyclist with a higher speed keeps a constant mean distance from the curb. However, for the interaction scenario the current approach could be changed. This research clearly shows that to reduce risk the time of interaction must be reduced, thereby increasing overtaking speed even in the shorter lateral distance scenarios increases safety of operation.

6.3 Scientific contribution

-Assessment of the change of cyclist's behavior and cyclist risk perception in the interaction with automated vehicle.

There is limited practical evidence and research about cyclist perception of the interaction scenarios with automated vehicles. The master thesis research contributes to cover this scientific gap. The research shows the difference in perception of automated overtaking and manual overtaking scenarios and no clear difference in perception of automated or manual driving in manual mode. The research also shows changes in cyclist behavior in interaction with automated vehicles, which points out for AV developers the need to change the automated vehicle programmed behavior. Additionally, this research shows that the basic trust to automation changes over the time of experiment, showing that familiarity influences the trust to AVs and that most of participants, even from the TU Delft University, are not fully familiar with the concept of automated driving. It is important to mention that the methodology used for assessment of cyclist behavior can be used to assess interaction between any other road users.

-Assessment of the correlation between Subjective Risk, Trust and Objective Risk and illumination of other influencing attributes.

The study made a step in understanding the perception of cyclist of risk levels. The research shows that overall the cyclist perception of the risk in interaction scenarios matches with the calculated Objective Risk. However, looking more precisely there is a clear mismatch between the moment of the highest Objective Risk and the moment of the highest perceived risk. Furthermore, the reaction of cyclist on risk (increasing speed, decreasing distance to the curb) shows a clear misunderstanding of the processes of appearing risk. Besides investigating correlations between risks and trust, the research also looked at other influencing independent parameters. A contribution to the existing body of research is made with the quantitative explanations of the correlations between dependent and independent variables with the use of GLMM equations.

-Implementation of the safety algorithm for the Objective Risk assessment

The novel concept for risk assessment named PDRF was not largely verified with existing field experiments in the existing literature. The master thesis research is one of the few verifications for the PDRF, especially with respect to Kinetic Risk, which is the risk originated from the interaction with moving objects on the road. The thesis research clearly approves the possibility for this risk matrix to reflect the interaction between moving objects. Regarding static objects, the master thesis investigates the value of the road barrier type sensitivity factor (k) for the green grass and asphalt pavements. Regarding the kinetic field, the research shows that the interaction time is an important attribute of the interaction. The interaction time can be included in the calculation of the probability of a collision, as with a longer interaction time the behavior of the cyclist changes to less safe.

6.4 Research limitations and recommendations for improvement.

Data collection

- The experiment is a controlled field experiment, the design of the experiment could affect the behavior of participants. To increase the credibility of the experiment, the naturalistic experiment should be used.
- The ethical committee put restrictions on the experiment conditions. Only experienced cyclists were allowed to be invited for the experiment. In a group of experienced cyclists, the experience level may vary. Looking at the data analysis, we can assume that trust may be correlated with the experience level. Thus, for future research it might be beneficial to include questions verifying the cycling level of experience.
- During the experiment data was lost. Data from some rides was not available, due to an equipment power loss. To avoid loss of power the car breaking must be done gently. Not all participants could finish all rides, due to the bad weather conditions, therefore an additional day of experiment can be planned in advance as a backup plan.
- The vehicle GPS made a lateral distance accounting error due to the unfavorable conditions in the troposphere. The mismatch was eliminated using the local coordinates for calculation of PDRF.
- The experiment vehicle was not an automated vehicle. Even though participants perceived the experiment as a realistic, the vehicle behavior with the human driver differs from the behavior of automated driving without a human inside. Also limited variations in the behavior of human driver is possible from ride to ride. To prevent significant changes in the behavior of a car, a second driver checked the overtaking speed and made sure the car is overtaking on the required distance.

Data analysis

- The Subjective Risk Value and Trust were collected one time per ride, which means that these measurements are discrete. It is not fully known for which point of time in a ride the participants reflect a certain reported value of risk and trust. For the trust parameter this was a minor issue, because trust represents the basic trust, while for subjective risk discrete nature of collected data was a disadvantage. To compare Subjective Risk with independent parameters, which were collected continuously, each independent parameter was recalculated to three discrete values: min, mean and max. The analysis shows that this method does not fully cover the correlation between parameters. Thus, future research can explore to implement standard deviation discrete parameter or to collect subjective risk values as a continuous data. It also worth mentioning that the self-reported risk level was not fully explanatory, as the size of the risk scale influenced participants. In the pilot-experiment the scale had a step of 10% and cyclist reported risks of 20% and 30%, which was on the 2nd and 3rd place in the scale, while during the main experiment the scale had a step of 5% and participants reported risk levels of 10% and 15% which is again on the 2nd and 3rd place in the scale. Future research can apply continuous data collection instead of self-reported, for example with galvanic skin response device or eye-tracker devices. The master thesis research proves that the position on the lane reflects the subjective risk level.

- In the literature no evidence was found for the k value of the Static Field PDRF for the green grass pavement, so the k value was assumed in a way that the Objective Risk was reduced on 10%. This assumption was rejected. It did not affect the results, because the relation between Objective Risk levels on the green grass side and asphalt side was shown, and the risk is a relative value. However, for future research the k value has to be corrected based on the findings of the master thesis research.
- The data set for this analysis was not extensive. For some analyses the number of observations were equal to 10 which could negatively affect the predictive power of statistical tests. Researchers could use larger samples as they provide better approximation to the whole population.

6.5 Further research

Scientific perspective

- One of the key findings of the study is the positive relation between the risk level and time of the interaction. However, at the high overtaking speeds, vehicle produces air pressure that may affect cyclist's balance and decrease safety of interaction. This research focused on the accelerative overtaking in which the significant speed difference is not possible. Larger speed differences are relevant for flying overtaking, when the vehicle approaches the cyclist with a higher speed and overtake without following the object (Dozza et al., 2016b). Further research may focus on analyzing higher overtaking speeds.
- The research made a first step in understanding the cyclist subjective risk. It was proven that a certain mismatch exists between the Subjective and Objective Risks, however the data collection captured only discrete values of Subjective Risk. Further research can include continuous values of the Subjective Risk.
- The study points out the differences in the behavior of cyclist due to the right-hand side objects, the research included a curb with a green-grass and a curb with an asphalt. Further research can be held on other infrastructure types with the aims of investigating changes in user behavior and proposing k (sensitivity due to the road boundary type) values for the PDRF.
- The research shows that the time of interaction is important for assessing kinetic risk. This finding can be further implemented in PDRF to improve the probability part.
- Participants mentioned the size and noise characteristics of the vehicle as a second most influencing factor on the Subjective Risk. The methodology proposed in the master thesis research can be directly applied to evaluate interaction with other types of road users, including vehicles larger in size and with louder engines.

Practical perspective

- The research outcome can be used by governments and the CBR to increase awareness of the cyclist and drivers about the nature of objective risk. The series of training can be organized in schools and driving courses to explain the mechanisms that generate risk and influencing factors. Potentially this educational program might decrease the number of accidents.
- Automated vehicle manufacturers can use the data collected from the experiment for the automated vehicle learning. The GLMM regression equation may be an input to the algorithm used for programming the vehicle behavior and the data collected during the experiment may be an input for the modelling that will teach the AV when to overtake and which interaction scenario to choose in different driving conditions. Also, the real-road experiment data can be used for the verification of the novel driving algorithms.
- The research proposes a method for assessing the risk of interaction between cyclist and automated vehicle. The methodological steps can be further applied to assess the risk of interaction between other road users. Especially this method will be applicable to the interaction between pedestrians and automated vehicle.

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Scientific Paper

Safety assessment of the interaction between an automated vehicle and a cyclist.

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Abstract

The operation of automated vehicles in shared areas requires attention with respect to the interaction between AVs and vulnerable road users, including cyclists. Currently, the programmed interaction behavior of AVs is based on the knowledge of the interaction between conventional vehicles and cyclists. However, cyclists may react differently to conventional and automated vehicles. Therefore, this research applies field test experiment to investigate the risks resulting from the interaction between cyclist and an AV. Four possible interaction scenarios were investigated in within-subject design with overtaking speed, overtaking distance and right-hand side objects as attributes. Objective Risk is assessed using the Probabilistic Driving Risk Field and Subjective Risk is assessed based on the self-reported values, cyclist behavior and trust. Results show that in general following has less risk than overtaking. Automated following and manual following have the same level of Objective and Subjective risks, while the automated overtaking has higher risk than manual overtaking. However, results also show that a larger interaction time leads to an increase in cycling speed and decrease in the distance to the curb. Furthermore, in the following maneuver the interaction time is higher than in the overtaking maneuver. Besides high time of interaction, closer overtaking distance and green grass on the right-hand side affect the increase in subjective and objective risks.

Keyword: •Automated Vehicle •Vulnerable Road Users •Subjective Risk •Objective Risk

Introduction

The operation of automated vehicles (AV) on shared roads means a constant interaction with road users. The interaction with the vehicle drivers is possible for automated vehicles, as vehicle drivers can share their intentions explicitly with turning signals and backup lights. Non-motorized modes of transport, namely cyclists and pedestrians, mostly use implicit communication channels such as eyes sign direction (Lagstrom & Lundgren, 2015), which is not yet possible for recognition for automated vehicles. To prevent misunderstanding in communication between AVs and Vulnerable Road Users (VRU), AVs are currently programmed in a way to minimize their interactions with vulnerable road users. In interaction with cyclists, one of the possible programmed behavior for the AV is to follow the cyclist at a rider speed (I-AT, 2019). Such a behavioral approach is not efficient in terms of traffic operation performance. In addition, cyclists may perceive being followed by a vehicle as dangerous.

Previous studies investigated ways for safe communication between AVs and non-motorized road users focuses on the interaction with pedestrians. Lagstrom & Lundgren (2015), Rodriguez Palmeiro et al. (2017) Böckle et al., 2017; Habibovic et al., 2018; Merat et al., 2017 show that pedestrians generally reported feeling less safe and behave more cautiously when interacting with AVs. There are very few studies focusing on the interactions between cyclists and AVs. Hagenzieker et al. (2018) conducted a questionnaire study on the behavior of cyclist. Participants were asked to study photos of automated vehicle with different signs. The purpose of the research was to investigate if the cyclist could correctly interpret when automated vehicles noticed them and whether an automated vehicle would stop for them. Researches show that the cyclist interacted more confidently with conventional vehicles than with automated ones (Hagenzieker et al., 2018). Even though pedestrians and cyclists are both non-motorized modes of transport and may have similarities in their behavior, cyclists still have special behavioral features.

Minimizing the risk of interaction between AVs and Cyclist requires an investigation of the changes of the Subjective and Objective risks due to the vehicle maneuvers and driving modes. It is also necessary to investigate the changes in the behavior of cyclist according to time of interaction and interaction with conventional or automated vehicle. Therefore, the research question can be formulated as follows: *Which interaction scenario minimizes Subjective and Objective Risks appearing when an automated vehicle approaches a cyclist from behind?*

In the research, passing interaction scenarios were considered, that refer to the situation when a cyclist and a vehicle are moving in the same direction. In case the automated vehicle is approaching the cyclist from behind, two sub-scenarios emerge. The first is following, i.e. when the automated vehicle approaches the cyclist from behind and moves with the cyclist speed, and the second is overtaking, i.e. when the automated vehicle passes the cyclist. The literature review highlights a gap in the knowledge about cyclist reaction on the maneuvers of the automated vehicle. In order to consider changes in the cyclist reactions on manual and automated operation modes, this research includes four scenarios: automated following, automated overtaking, manual following and manual overtaking.

On the risk of interaction besides the exact vehicle operation scenario also influence interaction attributes.

For the attributes of the vulnerable road users and automated vehicle interaction, research were mainly conducted on the pedestrian decision to cooperate with AVs. With respect to the decision to cross the road in front of automated vehicle, the highest influencing factors are speed of the vehicle and distance to the AV (Oxley, Ihsen, Fildes, Charlton, & Day, 2005; Rodríguez Palmeiro et al., 2018; Yannis, Papadimitriou, & Theofilatos, 2013). Other factors influencing on the pedestrian decision to cross in front of an AV are driver inattentiveness (Rodríguez Palmeiro et al. (2018)), the vehicle deceleration level, familiarity of environment for pedestrian, weather conditions, traffic volume level (Lagstrom & Lundgren, 2015), the size of the automated vehicle, the gender of the pedestrians and whether pedestrian crossing alone or in a group of people (Yannis et al., 2013).

The attributes corresponding to the overtaking maneuver were mainly assessed from the side of the vehicle drivers. Research from Weddell (2012) shows that the lateral distance of passing depends on the speed of the overtaking vehicle, the presence of an oncoming traffic, the size of the overtaking vehicle, the distance of the cyclist to the curb and the width of the bicycle lane. The literature shows a correlation between the speed of an overtaking vehicle and the distance that drivers keep to the cyclist. With a speed of 40 km/h drivers accept overtakings with passing distance of 1-1,5 m (Parkin & Meyers (2010) of Parkin & Schackel (2014)), while for the speed of 60 km/h and higher the passing distance increase to the 2-2,5 m (Debnath, Haworth, Schramm, Heesch, & Somoray (2018), Dozza et al., (2016)). Besides the characteristics of the overtaking maneuver, the gender of a cyclist affects the distance of overtaking. Drivers of conventional cars prefer to keep more distance from female cyclists than from a male cyclists (Chuang, Hsu, Lai, Doong, & Jeng, 2013; Walker, 2007). Chuang et al. (2013) found that a longer passing time influence on the observed increase in wheel angle and speed of cyclist.

As a result of literature review following attributes were chosen for the further analysis: overtaking lateral distance, overtaking vehicle speed, right hand side objects.

Research methodology

The data collection method of the research is a field experiment. Using the data collected during the experiment the Objective and Perceived risks were calculated. The objective risk was captured with the Probabilistic Driving Risk Field safety algorithm. Perceived risk was assessed using subjective risk, trust and cyclist behavior, where cyclist behavior is represented by the cyclist speed and cyclist distance to the curb. Next, to verify how the target variables related to the attributes, statistical analysis was conducted, including preliminary analysis, correlation analysis, regression analysis, graphs analysis.

Experiment setup and data collection

The experiment consists of two parts – a pilot experiment and a main experiment. Results of the pilot experiment provide improvements for the design of the main experiment. The main Experiment took 3 days, included 25 participants (13 males and 12 females) from the same age group (mean=25,4; std.=1,3), each participant did 10 rides. Four interaction scenarios were tested: automated following, automated overtaking, manual following and manual overtaking. Each scenario contains 3 within-subject variables (2 levels each): overtaking speed, overtaking distance, right hand side objects.

During the experiment equipped bicycle and equipped vehicle were used. The bicycle was equipped with 3 lidars, 2 cameras and GPS, and accelerometer sensors. The positioning of the sensors can be seen in the figure below. The experiment vehicle was equipped with GPS, accelerometer and camera. To collect a sufficient number of measurements in an overtaking maneuver, Lidar and GPS sensors collect 5 measurements in 1 second. The experiment vehicle was manually driven; however situations were pre-specified for participants when vehicle is in automated mode and when vehicle is in manual mode.

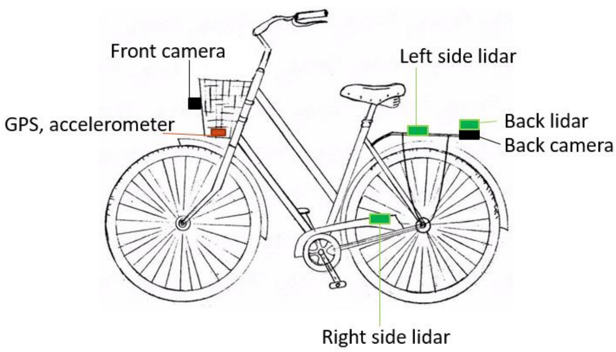

Figure 54: Sensors placement at bicycle

The data collected during the experiment are summarized in the table below. Using the questionnaire self-reported Trust and self-reported Subjective Risk were collected. Using sensors, the position (lateral and longitudinal) and the speed of the vehicle and cyclists were obtained. These measurements were used as an input to calculate objective risk. Additionally, the distance to the curb were obtained for the cyclist.

Table 27: Collected data

		Trust Level	***Subjective Risk Level***	***Objective Risk Level***	***Distance to the Curb***	***Speed***
			%	***Joules***	***Meters***	***Meter/Second***
Number of observations	Overall	242	242	80	222	100
	Per scenario: Automated following Automated overtaking Manual following Manual Overtaking	60	60	20	55	25
	Per scenario with a certain attribute of overtaking speed/distance	30	30	10	27	12
*Number of participants (25 participants did 10 rides; each participant did 4 scenarios)						

Objective risk assessment

The objective Risk was assessed with the Probabilistic Driving Risk Field (PDRF) safety approach. The PDRF is more sophisticated method compared to other Surrogate Measures of Safety (SMoS). This is because the PDRF has severity and probability components, which better reflect different situations (Bhusari, 2018) . For instance, some interactions with high severity magnitude do not result in an accident and interactions resulting in accidents do not always have the same magnitude and effects. Secondly, the PDRF can consider simultaneously the risk of collision with static and kinetic objects, which enhances the reality of risk modeling for interactions with different objects. This approach also allows to combine both lateral and longitudinal dimension risks simultaneously (Farah, Bhusari, Gent, Freddy, & Morsink, 2019).

The Probabilistic Driving Risk Field (PDRF) safety approach models the risk situation as a threat that an object S experiences from object C, designed as an influence field. The PDRF include

Potential field strength and Kinetic field strength. The Potential Field Strength is associated with the threat from the static road objects. The kinetic risk field strength is associated with moving road objects (Mullakkal Babu, Wang, Arem, & Happee, 2017). The Total Risk combines risks posed by multiple road objects based on the superposition property of fields (Mullakkal Babu et al., 2017).

The Potential Risk can be calculated using the following formula:

$$R_{b,s} = 0.5kM(V_{s,b})^2 \cdot max(e^{\frac{-|r_{s,b}|}{D}}, 0.001)$$

The crash severity is represented by the term $0.5kM(V_{s,b})^2$. The severity is the magnitude of the crash energy that appears in the event of an accident between objects S and B. The crash probability is defined by the term $e^{\frac{-|r_{s,b}|}{D}}$ which ranges between 0 and 1.

Where: s – is a dynamic object experiencing influence from the static object.

b- is a static object influencing the dynamic object s.

k- is the parameter of the rigidity of the road boundary object with range from 0 till 1, where k=1 entail that the static object has infinite mass and is not deformed in case of an accident. For the side of the road with the curb and an asphalt pedestrian path was used k=0,61 Mullakkal Babu et al. (2017) and for the side of the road with the curb and the green grass side were used k=0,55.

M- is the mass of the dynamic object s.

$V_{s,b}$ – is the velocity of the dynamic object S along $r_{s,b}$

$r_{s,b}$ – is the vector of the shortest distance between dynamic object s and static object b

D – is a steepness of descent of the potential risk field. For the master thesis research: $D = \frac{W}{14}$, where W is the width of the object s. The collision probability reaches a value of 0.001 in the center of the lane.

Kinetic Risk is represented by the following formula:

$$R_{n,s} = 0.5M_s\beta^2|\Delta V_{s,n}{}^2| \cdot p(n,s)$$

Where S – is a dynamic object that is experiencing risk from another dynamic object.

n- is a dynamic object that influence on the considering object S.

M_s – is a mass of the dynamic object.

$\beta = \frac{M_n}{M_s+M_n}$ represents a mass ratio of the interacting objects.

$\Delta V_{s,n} = V_s - V_n$ denotes the counteracting velocity between dynamic objects S and n.

p(n,s) - the probability of a collision. The collision appears if two objects come at the same place at the same time. Following that, the collision probability is characterized by a spatial overlap. The crash probability changes in a range from 0 to 1.

The collision probability likelihood is related to the probability of the object n acceleration. We know the trajectory of s and predict the trajectory of n. As the trajectory of n is unknown, the acceleration is treated as a random variable. The variability of acceleration is represented as a normal distribution and is equal to the relative likelihood of occurrence. The collision likelihood can be found:

$$p_L(n,s|\tau) = N(\frac{\Delta X - \Delta V_x \cdot \tau}{0.5 \cdot \tau^2}|\mu_x, \sigma_x) \cdot N(\frac{\Delta Y - \Delta V_y \cdot \tau}{0.5 \cdot \tau^2}|\mu_y, \sigma_y)$$

Where:
N- is probability density function
μ – is the mean of the distribution
σ- is the standard deviation of the distribution
$\Delta X = X_s - X_n$; $\Delta Y = Y_s - Y_n$ – relative spacing in longitudinal and lateral directions
$\Delta V_x = V_{X,s} - V_{X,n}$; $\Delta V_y = V_{Y,s} - V_{Y,n}$ – relative velocity in longitudinal and lateral directions
The reachable state for interacting objects can be represented as quadrilateral polygon. The zone O of potential collision zone is defined using the geometry of two interacting static objects. The overlapping region O also has the shape of a polygon, as shown on the figure below. The region O is converted to acceleration domain by the following formula:

$$A_x^c = \frac{(x^c - x_n(0)) - V_{x,n}(0) \cdot \tau}{0.5 \cdot \tau^2}$$

$$A_y^c = \frac{(y^c - y_n(0)) - V_{y,n}(0) \cdot \tau}{0.5 \cdot \tau^2}$$

Where x^c, y^c denotes the corner positions of overlapping region O.

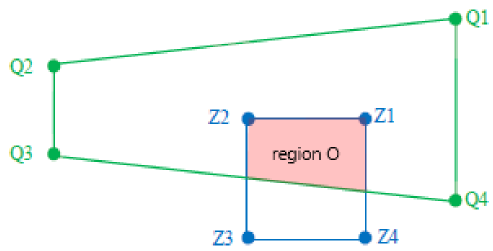

Figure 55: Geometric representation of polygons (Mullakkal Babu et al., 2017).

After the acceleration domain of the overlapping region O and the collision likelihood are found, the collision probability can be obtained by integrating the joint acceleration distribution over A0: $p(n,s|\tau) = \iint_{A0}(N(A_x|\mu_{x,}\sigma_x) \cdot N(A_y|\mu_{y,},\sigma_y) \cdot dA_x \cdot dA_y)$

Subjective risk assessment

The interaction process demands reliance on the system. Failures appears if users misuse automation by over-trusting the system, or if users disuse automation system by under-trusting it (Hoff & Bashir, 2015). Lee & See, (2004) reported that people tend to over-trust novel automated systems. Trust is not directly observable, which means that people can still cooperate with an automated system even without trusting it (Körber, 2019; Mayer, Davis, & Schoorman D., 1995). People who trust the system and people who do not trust the system can behave similarly. Data from sensors that collect skin response and heart rate cannot give useful insights on trust. As the level of risk in the field experiment is similar to daily stress (Rodriguez Palmeiro et al., 2017), only self-reported facts can reflect the real levels of trust and risk. Therefore, the questionnaires were applied to evaluate confidence of participants in response to automated vehicles. The trust was assessed using the Körber (2019) questionnaire on trust to technologies, which include 6 parameters: reliability; predictability; familiarity; intention of developers;

propensity to trust and trust in automation. Besides, trust also the behavior of cyclist was examined. Cyclist behavior is represented by the cyclist speed and cyclist distance to the curb.

Statistical analysis

The statistical analysis includes the following steps: descriptive analysis, correlation analysis, regression analysis, objective risk profile analysis. The statistical analysis shows the effects that the interaction attributes has on the risk levels.

As research input data has a hierarchical design and a nonparametric nature, the Generalized Linear Mixed Model (GLMM) (Dickey, 2010) was chosen for the data analysis. In hierarchical design, the data is repeatedly collected from the same individual and thus the observations for the same participant are correlated (West, 2009). The GLMM is a regression model that expresses the relationship of the target variable from the independent variables and works with the non-parametric target variable. The independent variables are described by fixed and random effect groups. The fixed effects stand for the parameters that are constant for the participant, as fixed parameters include all possible levels of parameter in the study design. For example, gender is a fixed effect (Starkweather, 2005; West, 2009). Random parameters have by-subject and by-item variation. By-subject variation is originated from the participants basic features of character and by-item variation accounts for the differences in the conditions of each levels of each independent variable (Winter, n.d.). To account for variation per participant the MLM assumes random intercepts for each participant. The equation of the Mixed Linear Model can be written as follows (Scharfenberger, 2013): $S = (\beta_0 \pm a_i) + \beta X_{ij} \pm b_j$

Table 28: Variables of the regression equation of the GLMM

Variables	***Description***
i	Subject
j	Plot
S	Dependent Variable Value
β_0	The intercept estimates mean value
a_i	The variability between participants
β	Fixed effects slope (rate of change), representing the difference to go down (or up) on the slope from one value of parameter to another (Winter, n.d.)
X_{ij}	Matrix of fixed effects
b_j	Variability within one participant

Results

In this section we discuss the results of the experiment, analyzed using descriptive analysis, correlation analysis, generalized linear mixed model and graphs.

Preliminary statistical analysis

Male participants show higher trust. The level of subjective risk is the same for both genders, however data on subjective risk for men is more consistent and does not exceed the median value. Male participants also have a higher level of objective risk, which might be connected with higher trust and lower subjective risk level. As male participants perceive interactions to be less risky, they tend to be less cautious and ride closer to the car at a higher speed. Besides gender of participants, also the weather conditions influenced target parameters. The day with the +20 and cloudy sky had trust levels slightly higher and the subjective risk lower than other days.

The experiment includes 4 interaction scenarios: automated following, automated overtaking, manual following and manual overtaking. Each of these scenarios was analyzed in terms of trust levels, subjective and objective risk levels, speed of cyclists and distance of cyclist to the curb. The boxplot analysis eliminates the interactions between parameters interesting for further analysis and later were conducted statistical tests and applied post-hoc Bonferroni correction. The following results were obtained.

The subjective risk level of the overtaking maneuver is higher than the subjective risk level of the following maneuver (Wilcoxon test p=0,001 a=0,01. The objective risk level of the overtaking maneuver is higher than the objective risk level of the following maneuver. (Wilcoxon test p=0,0014 a=0,0125) For driving in an automated mode, there is statistical evidence that the subjective risk for the overtaking with 3,5 m is lower than the subjective risk for overtaking with the 1,5 m. (Wilcoxon test, p=0,03 a=0,0125) For driving in manual mode, there is evidence that the subjective risk for the overtaking with 3,5 m is lower than the subjective risk for overtaking with the 1,5 m. (T-test, p=0,003 a=0,0125)

There is statistically significant evidence that the mean distance to the curb for the overtaking with 1,5 m is lower than the mean distance to the curb when overtaking with 3,5 m. (Wilcoxon test p=0,009 a=0,0125) In the scenarios with the same relative distance while overtaking and while following, the Subjective risk and Trust have the same value for both maneuvers. While the objective risk is higher for the overtaking than for the following (Wilcoxon p=0,001 a=0,0125)

In the experiment were two right hand side objects scenarios. The Distance to the Curb of cyclist riding on the side with the curb (asphalt) is higher than the Distance to the Curb of the cyclist cycling on the side of the green grass. (Wilcoxon p=0,000 a=0,025). The mean values of the Cyclist Speed are higher in the case of the grass on the RHS than in the case of the Curb on the RHS. (The Wilcoxon test p=0,000 a=0,025). The relative distance on the side of curb is lower than the relative distance on the side of grass. (the Wilcoxon p=0,025 a=0,025). The trust level for driving with the asphalt on the RHS is higher than the trust level for cycling with the grass on the RHS. (Wilcoxon test p=0,000 a=0,025)

Correlation analysis

The next step of analysis was related to the correlation analysis. Two correlation analysis for non-parametric data sets (Spearman correlation) were conducted. The first data set corresponds to the Objective Risk analysis with the continuous data set. The second data set corresponds to the Subjective risk analysis with the discrete data set.

There is a statistically significant negative association between subjective risk level and vehicle overtaking speed (p=0,005, r_s= -0,268), which indicates that an increase of overtaking distance is associated to an increase in subjective risk levels. However, after application of Bonferroni correction (corrected a=0,003) the null hypothesis could not be rejected. The strong negative correlation (p=0,000 r_s=-0,428 a=0,001) is between the trust Level and the subjective risk level. Furthermore, there is strong positive correlation between trust level and objective risk (p=0,000 r_s=+0,487 a=0,001) for mean and max objective risk, and a mean negative correlation (p=0,000 r_s=-0,324 a=0,001) between the trust and max distance to the curb.

The Spearman Correlation Matrix for the Objective Risk analysis shows a strong negative correlation between the Objective Risk and the Relative Distance (p=0,000, r_s=-0,778 a=0,005) and a strong positive correlation observed between the Relative Distance and the Relative Speed (p=0,000, r_s=0,574 a=0,005). The mean negative correlation is between the relative speed and Objective Risk (p=0,000, r_s=-0,28 a=0,005) and between the Distance to the Curb and Objective Risk (p=0,000, r_s=-0,11 a=0,005). A weak negative correlation appears between the Relative Distance and the Distance to the Curb (p=0,001, r_s=-0,077 a=0,005) and between the Relative Speed and the Distance to the Curb (p=0,002, r_s=-0,068 a=0,005).

Generalized Linear Mixed Model

To get insights on the relationship between non-parametric target parameters of trust, subjective risk, objective risk and independent variables, the Generalized Linear Mixed Model (GLMM) was applied.

For the GLMM model for the Subjective Risk Level dependency on the independent variables, only the random intercept was significant (Akaike Corrected Criterion = 604,688; Bayesian=628,634). According to this model the trust is the strongest individual predictor in the model. The regression equation for this model is as follows: $S = 39{,}942\, -\, 6{,}609y + 5{,}521x + 5{,}930z$

Where: Mean of the Subjective Risk = 39,942 for the participant with trust=0 and interaction scenario with no vehicle.

Model Term	Coefficient ▼	Std.Error	t	Sig.	95% Confidence Interval Lower	95% Confidence Interval Upper
Intercept	39,942	8,677	4,603	,000	22,700	57,183
Trust	-6,690	1,379	-4,852	,000	-9,430	-3,950
Gender=female	-0,702	2,831	-0,248	,805	-6,326	4,923
Gender=male	0,000[a]					
RHS=curb	-0,539	0,825	-0,654	,515	-2,178	1,099
RHS=grass	0,000[a]					
MaxObjectiveRisk	0,014	0,024	0,581	,563	-0,034	0,062
MeanDistancetotheCurb	-8,384	5,736	-1,462	,147	-19,782	3,013
MaxCyclistSpeed	-0,213	0,912	-0,234	,816	-2,025	1,598
InteractionScenarios=automated following	5,521	2,671	2,067	,042	0,214	10,828
InteractionScenarios=automated overtaking	5,930	2,825	2,099	,039	0,317	11,543
InteractionScenarios=manual following	3,186	2,790	1,142	,257	-2,358	8,729
InteractionScenarios=manual overtaking	4,265	2,844	1,499	,137	-1,387	9,917
InteractionScenarios=no vehicle	0,000[a]					

Probability distribution:Normal
Link function:Identity

[a]This coefficient is set to zero because it is redundant.

Figure 56: Fixed effects of the GLMM model for the Subjective Risk

For the GLMM model for the Trust Level dependency on the independent variables, the random effect of the Subjective Risk Level was significant. However, the best model fit got the model with the random intercept (Akaike Corrected Criterion =115,354; Bayesian=139,3). According to this model the strongest individual predictor is a lateral mean distance to the curb. The regression equation for this model has a following form: $S = 3{,}520 + 0{,}628x + 0{,}478y + 0{,}629z + 0{,}536g - 0{,}024h + 0{,}004k - 0{,}792m + 0{,}131n \pm 0{,}093$

Where, 3,520 is a mean value of the Trust Level for the participant experiencing the subjective risk level of 0, max objective risk of 0, riding with the distance to the curb 0 cm and max cyclist speed 0 on the interaction scenario with no vehicle. In this model was fins statistically significant (p=0,05) variability within rides of same participant equals to the 0,093.

Model Term	Coefficient ▼	Std.Error	t	Sig.	95% Confidence Interval	
					Lower	Upper
Intercept	3,520	0,459	7,662	,000	2,607	4,433
Gender=female	-0,215	0,251	-0,859	,392	-0,713	0,283
Gender=male	0,000[a]					
RHS=curb	0,065	0,056	1,157	,250	-0,046	0,176
RHS=grass	0,000[a]					
InteractionScenarios=automated following	0,628	0,118	5,307	,000	0,393	0,863
InteractionScenarios=automated overtaking	0,478	0,139	3,436	,001	0,202	0,755
InteractionScenarios=manual following	0,629	0,123	5,098	,000	0,384	0,874
InteractionScenarios=manual overtaking	0,536	0,141	3,797	,000	0,255	0,816
InteractionScenarios=no vehicle	0,000[a]					
SubjectiveRiskLevel	-0,024	0,005	-4,672	,000	-0,035	-0,014
MaxObjectiveRisk	0,004	0,002	2,125	,036	0,000	0,007
MeanDistancetotheCurb	-0,792	0,356	-2,225	,029	-1,500	-0,085
MaxCyclistSpeed	0,131	0,054	2,414	,018	0,023	0,238

Probability distribution:Normal
Link function:Identity

[a]This coefficient is set to zero because it is redundant.

Figure 57: Fixed effects of the GLMM model for the trust

The GLMM model for the Objective Risk dependency on the independent variables has random intercept as a random parameter (Akaike Corrected = 14,433, Bayesian = 15,512). For this model the strongest individual predictor is the interaction scenario with a manually following vehicle. The regression equation for this model is as follows: $S = 10{,}085 - 4{,}550x + 0{,}636y - 4{,}870z - 1h - 0{,}486g - 0{,}426k$

Where, 10,085 Joules of Objective Risk corresponds to the mean value of the Objective Risk for the participant experiencing the interaction with manually overtaking vehicle on the side of the road with green grass and cycling with a speed of 0 m/s and relative distance of 0 m.

Model Term	Coefficient ▼	Std.Error	t	Sig.	95% Confidence Interval	
					Lower	Upper
Intercept	10,085	1,721	5,861	,000	6,710	13,459
Gender=female	-0,496	1,375	-0,360	,719	-3,193	2,201
Gender=male	0ᵃ					
InteractionScenario=Automated Following	-4,550	0,516	-8,816	,000	-5,562	-3,538
InteractionScenario=Automated Overtaking	0,636	0,300	2,119	,034	0,047	1,225
InteractionScenario=Manual Following	-4,870	0,526	-9,252	,000	-5,903	-3,838
InteractionScenario=Manual Overtaking	0ᵃ					
RHS=Curb	-1,000	0,194	-5,146	,000	-1,381	-0,619
RHS=Grass	0ᵃ					
DistancetotheCurb	-0,353	0,856	-0,413	,680	-2,031	1,325
CyclistSpeed	-0,486	0,199	-2,435	,015	-0,877	-0,095
RelativeDistance	-0,426	0,033	-13,026	,000	-0,490	-0,361
RelativeSpeed	0,112	0,237	0,472	,637	-0,353	0,577

Probability distribution:Normal
Link function:Identity

ᵃThis coefficient is set to zero because it is redundant.

Figure 58: Fixed effects for the GLMM model for the objective risk

Graphical analysis of parameter changes along the route

The plot shows that overtaking maneuvers have higher values of objective risk than the following maneuver. However, the duration of the interaction time is higher in the case of the following maneuvers. Both interaction scenarios have higher values at the beginning of the route, when participants are getting used to the bicycle and did not yet stabilized their movement. The overtaking maneuvers have Objective Risk bursts at the phase of approaching to overtake and coming back to the lane. The minimal value part of the overtaking maneuver refers to the reduced probability of collision, given that objects moving parallel to each other have a low probability of collision. Automated and Manual driving modes have the same levels of objective risk for both vehicle maneuvers.

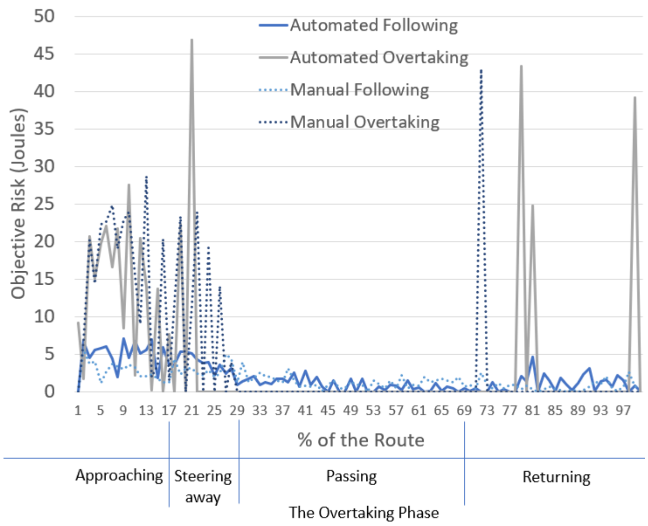

Figure 59: The Objective Risk along the route

In the overtakings, during the passing stage, cyclists start cycling closer to the curb, slightly increasing speed, then come back to the original distance and speed after the vehicle returns to the lane in front of the cyclist. The Distance to the Curb has slightly lower values for the Automated driving mode than for the Manual driving mode. The speed has higher values for the manual overtaking scenarios in comparison to the automated overtaking scenarios, which can be explained as the trust level for the manual driving is higher than for automated driving and thus the basic speed was always higher for manual driving that for automated driving.

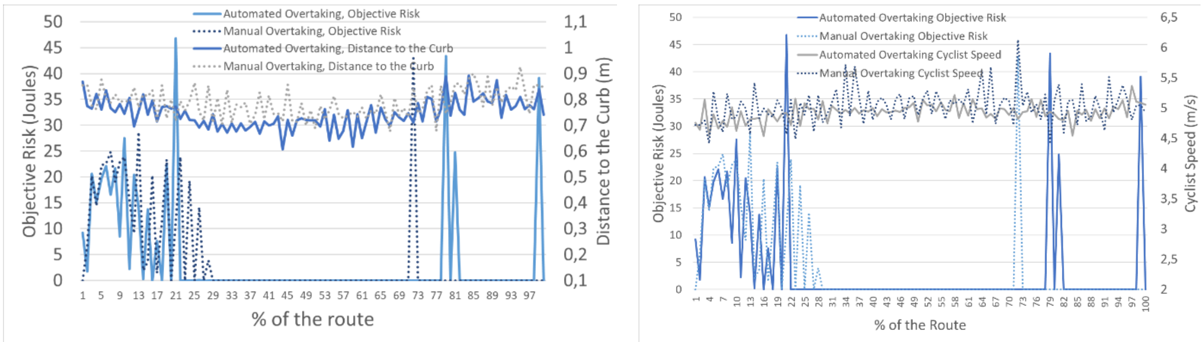

Figure 60: The Objective Risk, the Distance to the Curb and The Cyclist Speed along the route

In general, cyclists reach the highest speed in the middle part of the lane. When the cyclist goes closer to the curb or closer to the vehicle lane the speed drops. Overall, the speed level has a slight change with time, while the position of the cyclist on a bicycle lane (represented by the distance to the curb) varies significantly. This can be explained by the relation between speed and balance, which hampers speed variation.

Participants from the higher trust group have higher cycling speed during the whole time of the experiment and keep their position on the lane more coherent. These two characteristics are interrelated, as to keep a high speed a certain balance have to be reached and with variation of the position on a lane the balance can be lost. The mean trust group and low trust group cyclists have a similar speed range. However, the low trust group have a big variation in its position on the lane.

Conclusions

This section gives an overview of the conclusions reached during the research and a future research that can be conducted based on the study outcomes.

The research aimed to investigate changes in the behavior of cyclist due to interaction with the automated vehicles and recommend on the interaction scenarios resulting in the minimal subjective and objective risks. There is a clear evidence that the overtaking has a higher Subjective and Objective risk levels than the following. However, the time of the interaction has high impact on the cyclist behavior. Towards the end of the following scenarios, the cyclist increases the speed or cyclist starts looking behind to see the following vehicle, leading to losing balance and approaching the curb. In the overtaking scenarios, during the passing stage the cyclist reduces distance to the curb and increases speed, which results in a higher Objective Risk. The interaction time is much lower for the overtakings than for followings. Thus, we can conclude that for short distances the following is a safer option. Besides exact vehicle maneuver, also the operation modes have an influence on the risk levels. For the following scenario there is no clear difference between operation modes. For the overtaking scenarios, the automated mode has clearly higher risks levels than the manual driving.

The risk of the interaction scenario is also influenced by the available relative distance. The higher the distance the lower the risk. For the wide street of 3 meters the overtaking scenarios have the same subjective risk as the following option. Besides overtaking with a higher distance another recommendation could be to overtake with a high speed (in the research speeds below 40 km/h were assessed) to reduce the interaction time. Information about the right-hand side objects should be considered for deciding over the vehicle operation parameter. The streets with the green grass on their sides are perceived by cyclist as more dangerous.

Despite the promising results, this study has some limitations that could be improved in future research. The experiment is a controlled field experiment, conducted with 25 participants from the same age group. Researchers could use larger samples as they provide better approximation to the whole population and could use naturalistic experiment to eliminate changes in the behavior of participants due to the design of experiment. The experiment vehicle was not an automated vehicle. Even though participants perceived the experiment as realistic, the vehicle behavior with the human driver differs from the behavior of automated driving. Another limitation comes from the discrete nature of the Subjective Risk. Values were collected one time per ride and we do not know exactly which point of time in a ride reflects such reported value of risk.

Besides future research related to the limitation of the research, the study outcomes also gives input for the vehicle producers to improve the behavior of automated vehicle. The government or the CBR can use this study to increase awareness of the cyclist and drivers about the nature of Objective Risk.

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Appendix A: Experiment Setup

Consent Form for the master thesis research "Influence of automated vehicle actions on the joint risk level resulting from the interactions with cyclists."

Please tick the appropriate boxes	Yes	No
Taking part in the study		
I have read and understood the study information dated (20.06.2019) or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	○	○
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	○	○
I understand that during the experiment I will be asked to cycle on the road shared with the automated vehicle.	○	○
I understand that taking part in the study I give permission to be video recorded. Also, during the experiment I would be asked to fill in electronic questionnaires.	○	○
Video recordings will be transcribed as text, and after the end of the master thesis research all video files will be deleted.		
Use of the information in the study		
I understand that information I provide will be used for the master thesis report and scientific publications.	○	○
I understand that personal information collected about me that can identify me, such as the video recordings, will not be shared beyond the study team.	○	○
I agree that my information can be quoted in research outputs.	○	○
Future use and reuse of the information by others		
I give permission for the questionnaires and video files that I provide to be archived in the Royal Haskoning data base in anonymized transcript, so it can be used for future research and learning.	○	○

Signatures

________________	________________	________
Name of participant	Signature	Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

Oskina Maria		25 August
Researcher name	Signature	Date

Study contact details for further information: Maria Oskina, ms.maria.oskina@gmail.com
whatsapp: +79160121669

Figure 61: Consent Form

Introduction to experiment

Dear Participant of the Experiment,

You are about to participate in a field experiment as a part of a master thesis research. The Master thesis is aiming at analyzing the interactions between cyclists and an automated vehicle. Automated vehicle can operate both: in automated and manual mode.

During the experiment, you will be asked to cycle on the route. The route is represented below on the picture. Orange color arrows represent cycling route. Stars represent the organizers of the experiment. **The experiment will start near the green star.**

Figure 1: Experiment Route

During the experiment, you will be recorded on camera. Later, recordings will be used to conduct observation studies. All video files will be deleted after the end of the master thesis research.

You will be asked to fill in questionnaires, each questionnaire will take less than 2 minutes. You already received the first questionnaire. Other questionnaires will appear in different time during the experiment. Please, on the route, always make a stop near an organizer of the experiment (location represented by the star image on the map).

If during the experiment any difficulty occurs, you must immediately stop and inform the organizers of the experiment.

Thank you for the collaboration!
Enjoy the experiment!

Figure 62: Introduction to experiment

I-AT project questionnaire 1

1. What is your participant number?

2. What is your gender?

- Female
- Male

3. In the experiment, you will interact with the automated vehicle.
Please fill in the matrix for the automated vehicle system.

	Strongly disagree	Rather disagree	Neither disagree nor agree	Rather agree	Strongly agree
The automated vehicle system is capable of interpreting situations correctly.					
The automated vehicle system works reliably.					
I trust the automated vehicle system.					
An automated vehicle system failure is likely.					
The automated vehicle system is capable of taking over complicated tasks.					
I can rely on the automated vehicle system.					
The automated vehicle system might make accidental errors.					
I am confident about the automated vehicle system's capabilities.					

Done

Figure 63: Questionnaire 1

I-AT project questionnaire 2

1. What is the respondent number?

2. What was the level of risk that you experienced on this part of the route?

5 %	10 %	15 %	20 %	25 %	30 %	35 %	40 %	45 %	50 % and higher	N/A

Other (please specify)

Done

Figure 64: Questionnaire 2

I-AT project questionnaire 3

1. What is the participant number?

2. What is the scenario number?

3. How the vehicle was operated at this part of the route?

- ☐ Automatically
- ☐ Manually (human driver controlled)

4. What was the level of risk on this part of the route?

5 %	10 %	15 %	20 %	25 %	30 %	35 %	40 %	45 %	50 % and higher	N/A
★	★	★	★	★	★	★	★	★	★	○

Other (please specify)

5. Which parameters influence on the risk level you reported?

- ○ Distance to the vehicle
- ○ Speed of the vehicle
- ○ Attentiveness of the driver
- ○ Objects on the RHS
- ○ Vehicle characteristics (size/noise)
- ○ Vehicle driving mode (automated/manual)
- ○ Other (please specify)

6. Please fill in the matrix

	Strongly disagree.	Rather disagree.	Neither disagree nor agree.	Rather agree.	Strongly agree.
The system is capable of interpreting situations correctly.	○	○	○	○	○
The system state was always clear to me.	○	○	○	○	○
The system works reliably.	○	○	○	○	○
The system reacts unpredictably.	○	○	○	○	○
I trust the system.	○	○	○	○	○
A system failure is likely.	○	○	○	○	○
I was able to understand why things happened.	○	○	○	○	○
The system is capable of taking over complicated tasks.	○	○	○	○	○
I can rely on the system.	○	○	○	○	○
The system might make accidental errors.	○	○	○	○	○
It's difficult to identify what the system will do next.	○	○	○	○	○
I am confident about the system's capabilities.	○	○	○	○	○

Figure 65: Questionnaire 3

Figure 66: Equipped bicycle

Figure 67: Experiment location

Appendix B: Pilot-Experiment Statistical Analysis

Attributes influencing the risk level (self-reported by participants)

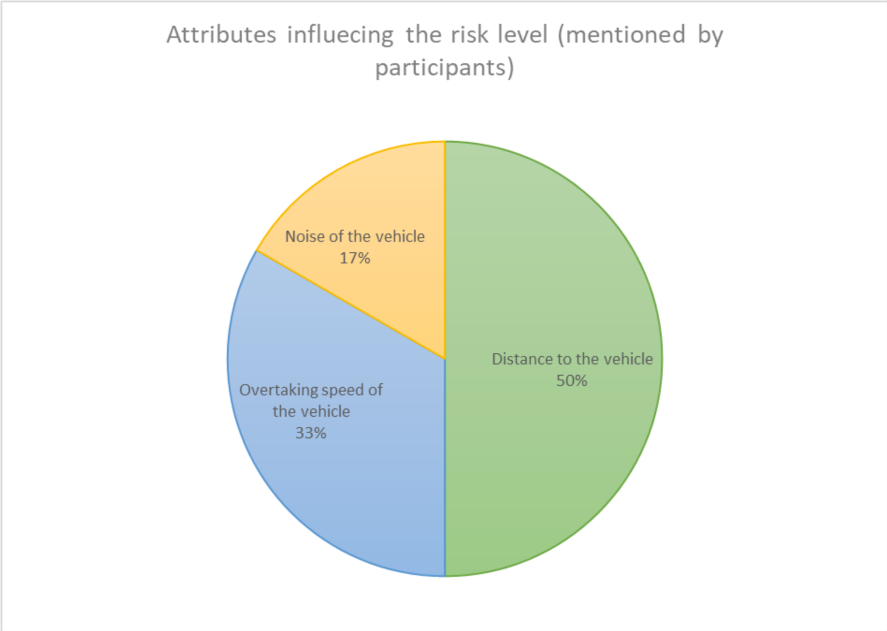


Figure 68: Attributes influencing the risk level (self-reported by participants)

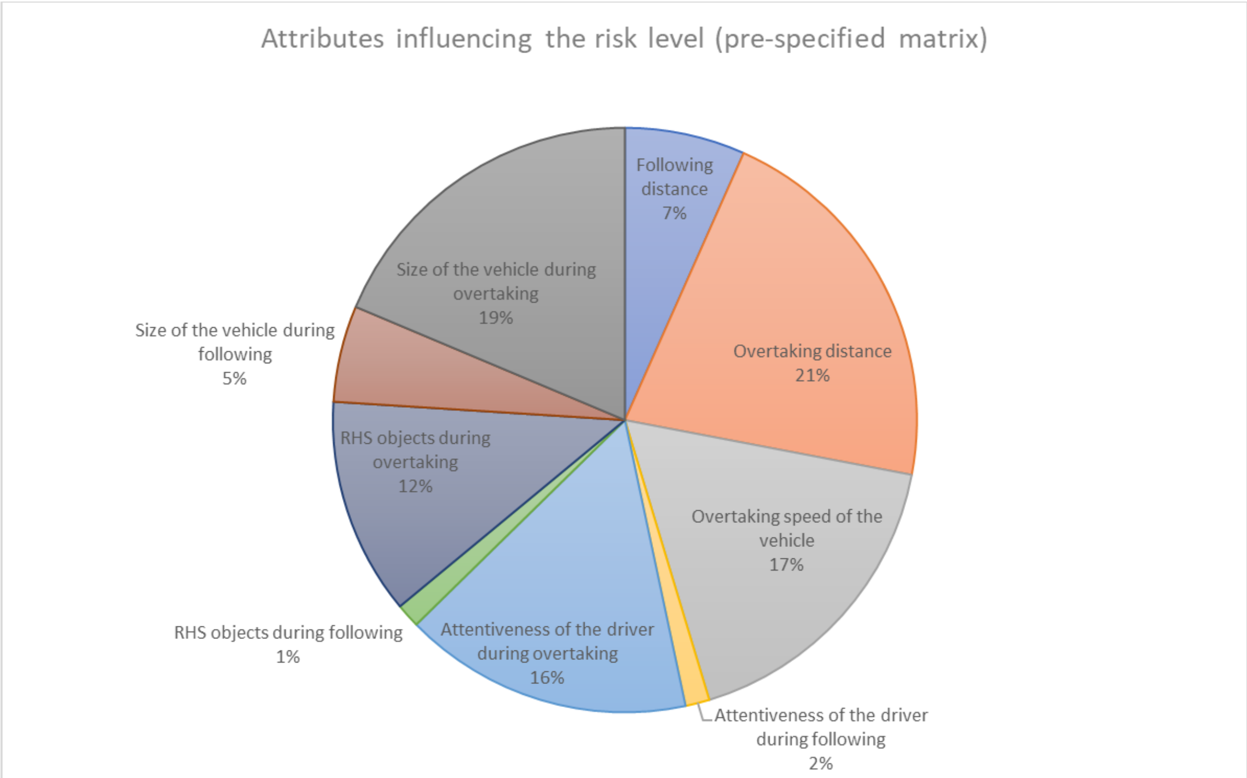


Figure 69: Attributes influencing the risk level (pre-specified by researcher)

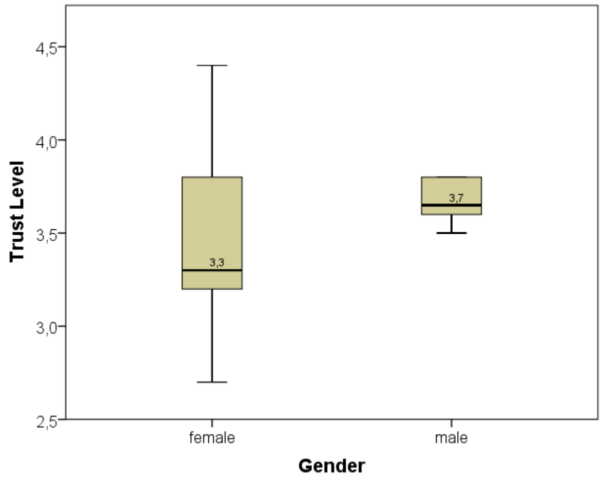


Figure 70: Dependence of the trust level in the gender of participants

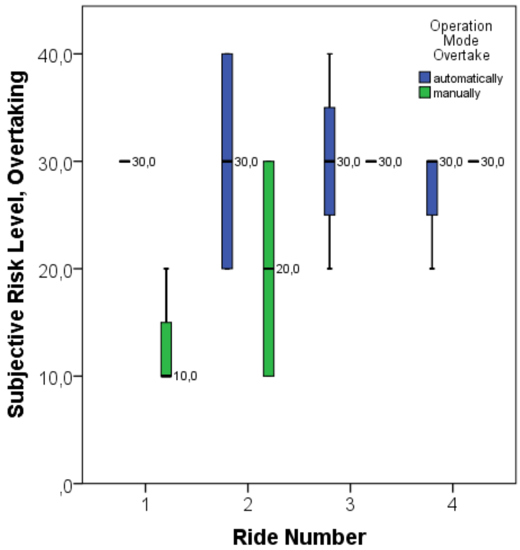


Figure 71: Dependence of the Subjective Risk Level, when Overtaking, on the Ride Number and Operation Mode of the Vehicle.

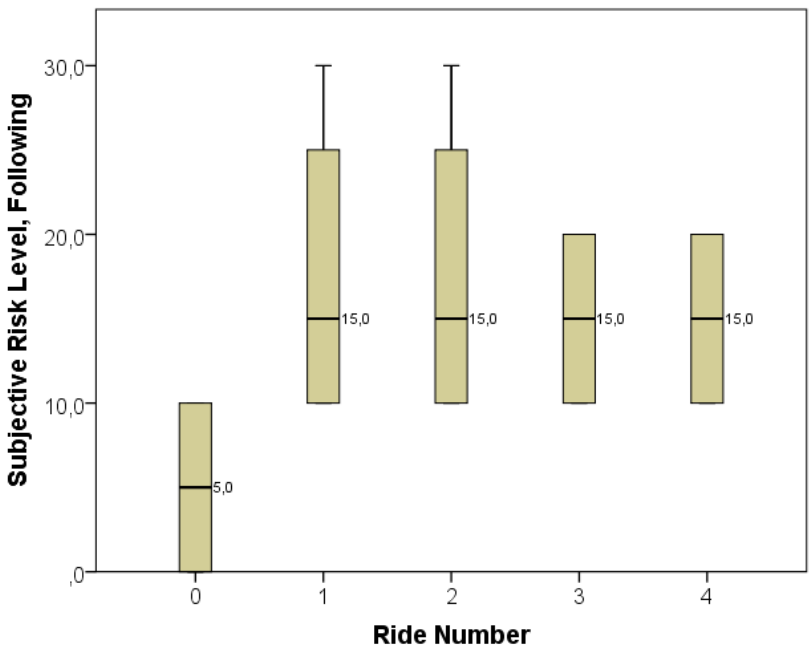


Figure 72: Dependence of the Subjective Risk Level, when Following, on the Ride Number.

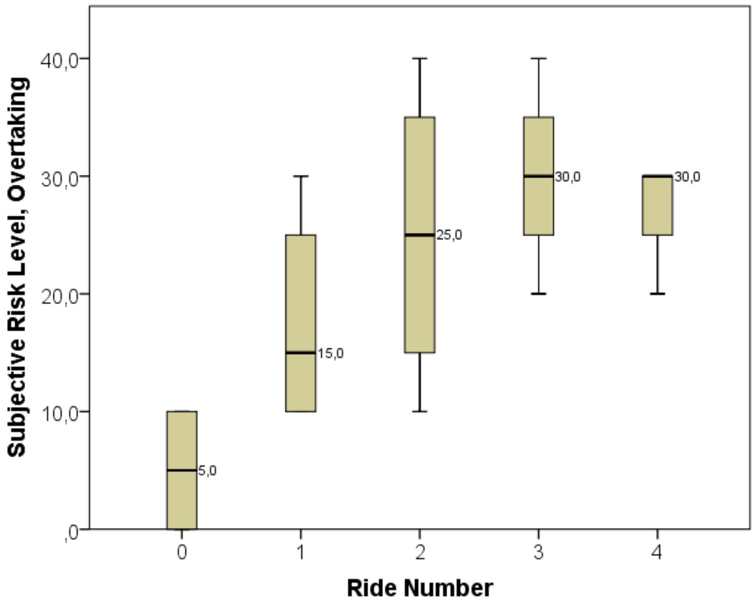
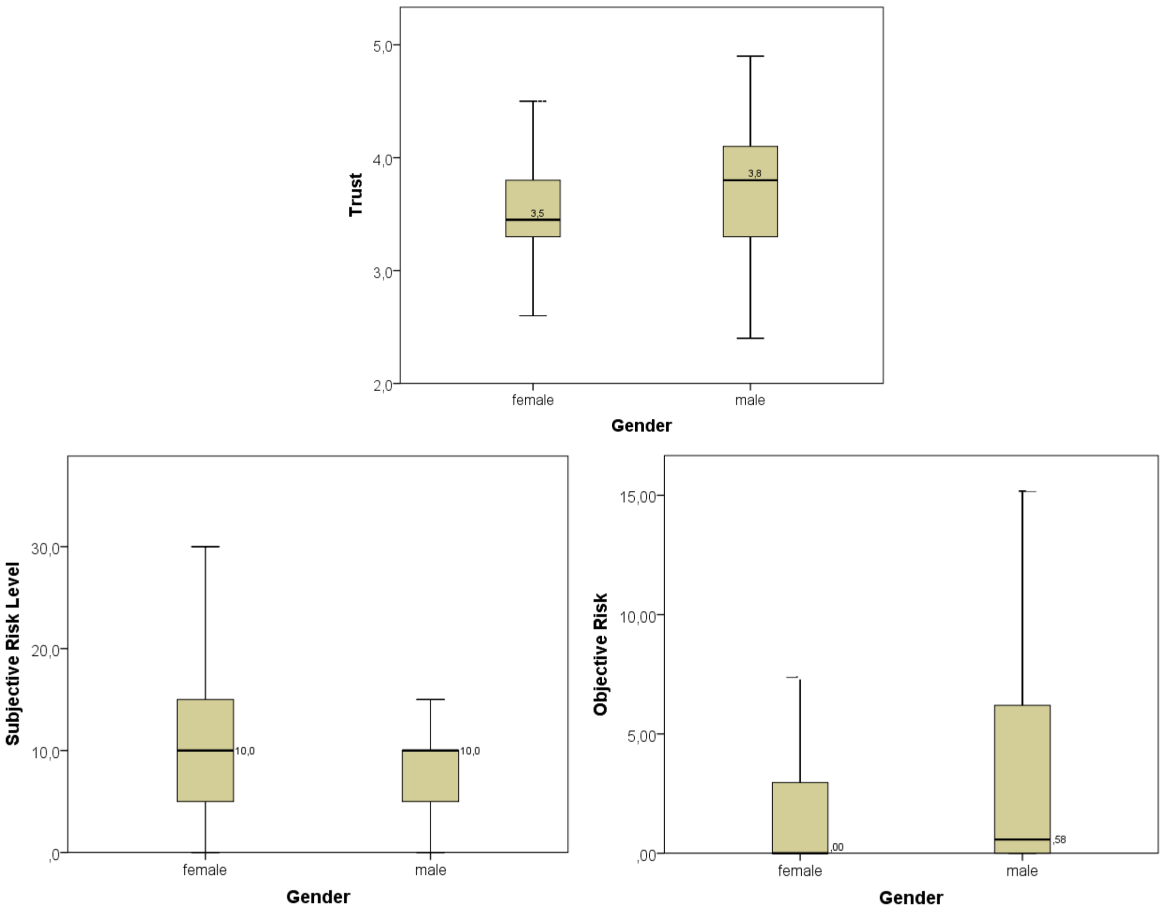


Figure 73: Dependence of the Subjective Risk Level, when Overtaking, on the Ride Number.

Appendix C: Main Experiment Statistical Analysis

Figure 74: Boxplot analysis of gender attributes



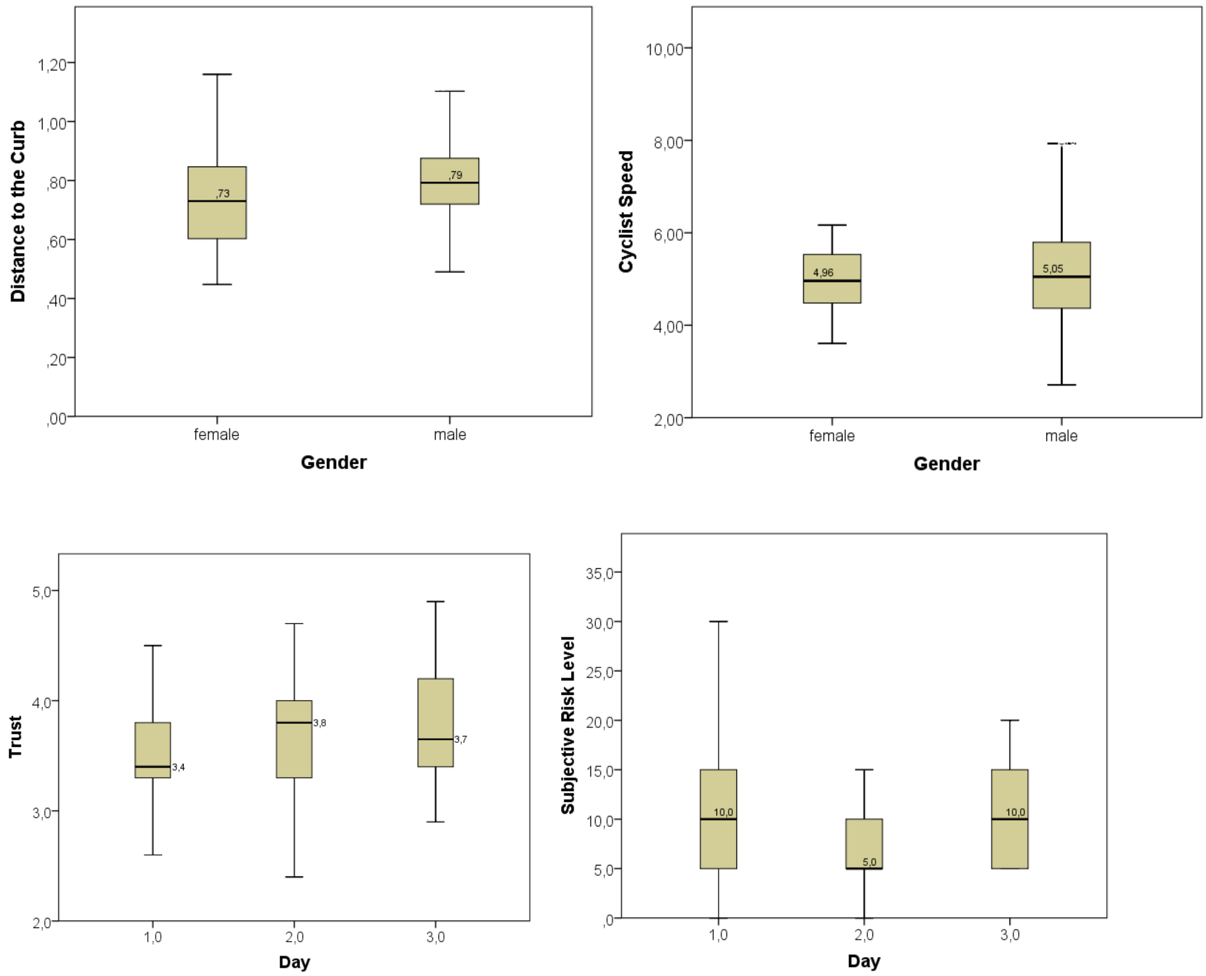


Figure 75: Boxplot analysis of the weather condition attributes

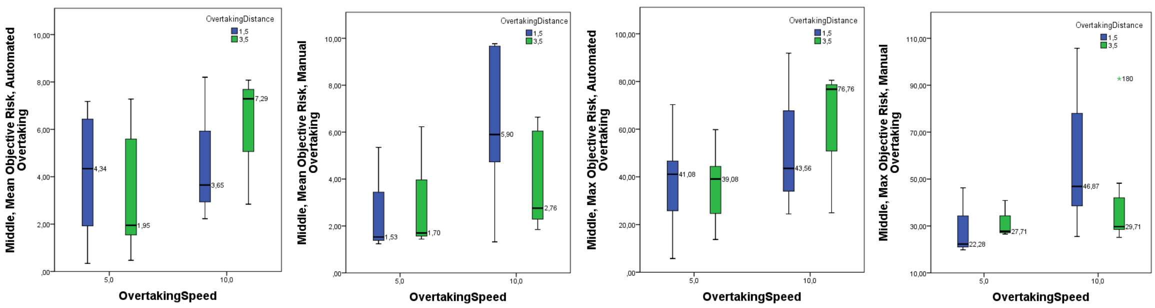


Figure 76: Dependence of the Objective Risk on Overtaking Speed and Overtaking Distance

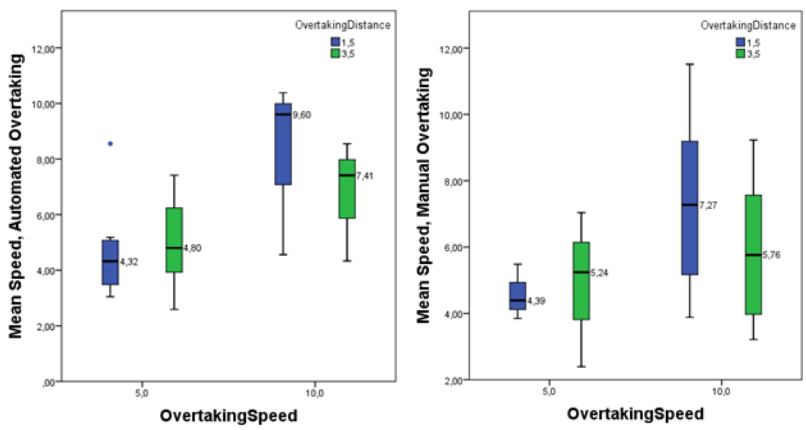


Figure 77: Dependence of the Cyclist Speed on Overtaking Speed and Overtaking Distance

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distributions of 1 Trust, 2 Trust, 3 Trust, 4 Trust, 5 Trust, 6 Trust, 7 Trust and 8 Trust are the same.	Related-Samples Friedman's Two-Way Analysis of Variance by Ranks	,161	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distributions of 1 MiddleMaxObjectiveRisk, 2 MiddleMaxObjectiveRisk, 3MiddleMaxObjectiveRisk, 4 MiddleMaxObjectiveRisk, 5 MiddleMaxObjectiveRisk, 6 MiddleMaxObjectiveRisk, 7 MiddleMaxObjectiveRisk and 8 MiddleMaxObjectiveRisk are the same.	Related-Samples Friedman's Two-Way Analysis of Variance by Ranks	,956	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distributions of 1 MiddleMeanObjectiveRisk, 2 MiddleMeanObjectiveRisk, 4 MiddleMeanObjectiveRisk, 5 MiddleMeanObjectiveRisk, 6 MiddleMeanObjectiveRisk, 7 MiddleMeanObjectiveRisk, 8 MiddleMeanObjectiveRisk and 3MiddleMeanObjectiveRisk are the same.	Related-Samples Friedman's Two-Way Analysis of Variance by Ranks	,070	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distributions of 1 SubjectiveRiskLevel, 2 SubjectiveRiskLevel, 3 SubjectiveRiskLevel, 4 SubjectiveRiskLevel, 5 SubjectiveRiskLevel, 6 SubjectiveRiskLevel, 7 SubjectiveRiskLevel and 8 SubjectiveRiskLevel are the same.	Related-Samples Friedman's Two-Way Analysis of Variance by Ranks	,824	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

Figure 78: Friedman tests for analysis of participants learning

Spearman Correlations

			Trust	Subjective Risk Level	Middle Part Min Distance	Middle Part Mean Distance	Middle Part Max Distance	Middle, Mean Objective Risk	Middle, Max Objective Risk	Middle, Mean Speed	Middle, Min Speed	Middle, Max Speed
Spearman's rho	Trust	Correlation Coefficient	1,000	-,428**	-,059	-,203**	-,324**	,487**	,448**	,137	-,065	,072
		Sig. (2-tailed)		,000	,384	,002	,000	,000	,000	,173	,520	,474
		N	726	726	222	222	222	100	100	100	100	100
	Subjective Risk Level	Correlation Coefficient	-,428**	1,000	-,166*	-,140*	-,045	,057	,112	-,037	-,059	-,030
		Sig. (2-tailed)	,000		,013	,037	,509	,574	,267	,716	,557	,770
		N	726	726	222	222	222	100	100	100	100	100
	Middle Part Min Distance	Correlation Coefficient	-,059	-,166*	1,000	,847**	,507**	-,003	-,046	,006	,017	-,071
		Sig. (2-tailed)	,384	,013		,000	,000	,980	,649	,953	,863	,482
		N	222	222	222	222	222	100	100	100	100	100
	Middle Part Mean Distance	Correlation Coefficient	-,203**	-,140*	,847**	1,000	,812**	-,148	-,196	-,059	,024	-,048
		Sig. (2-tailed)	,002	,037	,000		,000	,141	,050	,561	,815	,632
		N	222	222	222	222	222	100	100	100	100	100
	Middle Part Max Distance	Correlation Coefficient	-,324**	-,045	,507**	,812**	1,000	-,202*	-,261**	-,153	,048	-,001
		Sig. (2-tailed)	,000	,509	,000	,000		,044	,009	,130	,635	,994
		N	222	222	222	222	222	100	100	100	100	100
	Middle, Mean Objective Risk	Correlation Coefficient	,487**	,057	-,003	-,148	-,202*	1,000	,801**	,141	-,255*	,010
		Sig. (2-tailed)	,000	,574	,980	,141	,044		,000	,161	,010	,923
		N	100	100	100	100	100	100	100	100	100	100
	Middle, Max Objective Risk	Correlation Coefficient	,448**	,112	-,046	-,196	-,261**	,801**	1,000	,302**	-,104	,050
		Sig. (2-tailed)	,000	,267	,649	,050	,009	,000		,002	,304	,619
		N	100	100	100	100	100	100	100	100	100	100
	Middle, Mean Speed	Correlation Coefficient	,137	-,037	,006	-,059	-,153	,141	,302**	1,000	,058	,384**
		Sig. (2-tailed)	,173	,716	,953	,561	,130	,161	,002		,570	,000
		N	100	100	100	100	100	100	100	100	100	100
	Middle, Min Speed	Correlation Coefficient	-,065	-,059	,017	,024	,048	-,255*	-,104	,058	1,000	,584**
		Sig. (2-tailed)	,520	,557	,863	,815	,635	,010	,304	,570		,000
		N	100	100	100	100	100	100	100	100	100	100
	Middle, Max Speed	Correlation Coefficient	,072	-,030	-,071	-,048	-,001	,010	,050	,384**	,584**	1,000
		Sig. (2-tailed)	,474	,770	,482	,632	,994	,923	,619	,000	,000	
		N	100	100	100	100	100	100	100	100	100	100

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

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

Figure 79: Spearman Correlation Matrix for the discrete data

Correlations for discrete data

			Trust	Subjective Risk Level	Mean Objective Risk	Max Objective Risk	Overtaking Speed	Overtaking Distance
Spearman's rho	Trust	Correlation Coefficient	1,000	-,428**	,487**	,448**	,013	,103
		Sig. (2-tailed)		,000	,000	,000	,898	,318
		N	242	242	100	100	96	96
	Subjective Risk Level	Correlation Coefficient	-,428**	1,000	,057	,112	,026	-,268**
		Sig. (2-tailed)	,000		,574	,267	,803	,008
		N	242	242	100	100	96	96
	Mean Objective Risk	Correlation Coefficient	,487**	,057	1,000	,801**	,321*	-,069
		Sig. (2-tailed)	,000	,574		,000	,044	,671
		N	100	100	100	100	40	40
	Max Objective Risk	Correlation Coefficient	,448**	,112	,801**	1,000	,316*	-,087
		Sig. (2-tailed)	,000	,267	,000		,047	,595
		N	100	100	100	100	40	40
	Overtaking Speed	Correlation Coefficient	,013	,026	,321*	,316*	1,000	0,000
		Sig. (2-tailed)	,898	,803	,044	,047		1,000
		N	96	96	40	40	100	100
	Overtaking Distance	Correlation Coefficient	,103	-,268**	-,069	-,087	0,000	1,000
		Sig. (2-tailed)	,318	,008	,671	,595	1,000	
		N	96	96	40	40	100	100

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

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

Figure 80: Spearman Correlation Matrix for the discrete data

Generalized Linear Mixed Model

Figure 81: GLMM for the subjective risk

Target		Subjective Risk Level
Probability Distribution		Normal
Link Function		Identity
Information Criterion	**Akaike Corrected**	710,744
	Bayesian	752,325

Information criteria are based on the -2 log likelihood (640,109) and are used to compare models. Models with smaller information criterion values fit better.

All random parameters

Target		Subjective Risk Level
Probability Distribution		Normal
Link Function		Identity
Information Criterion	**Akaike Corrected**	604,688
	Bayesian	628,634

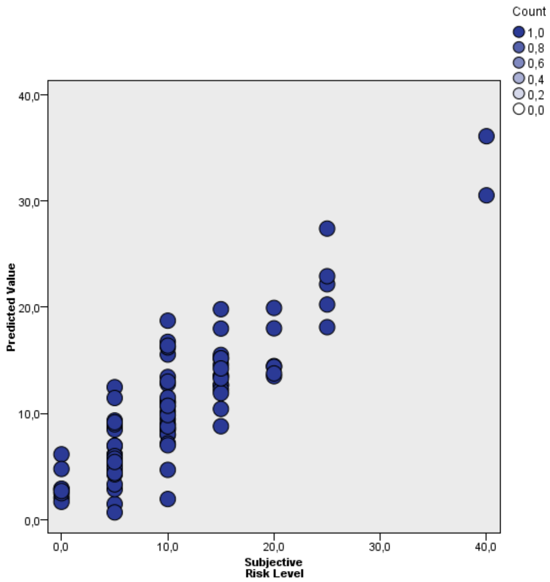
Information criteria are based on the -2 log likelihood (579,259) and are used to compare models. Models with smaller information criterion values fit better.

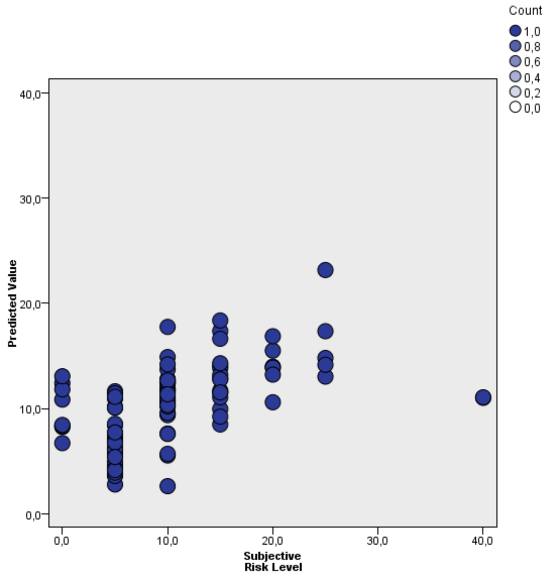
No random parameters

Target		Subjective Risk Level
Probability Distribution		Normal
Link Function		Identity
Information Criterion	**Akaike Corrected**	604,688
	Bayesian	628,634

Information criteria are based on the -2 log likelihood (579,259) and are used to compare models. Models with smaller information criterion values fit better.

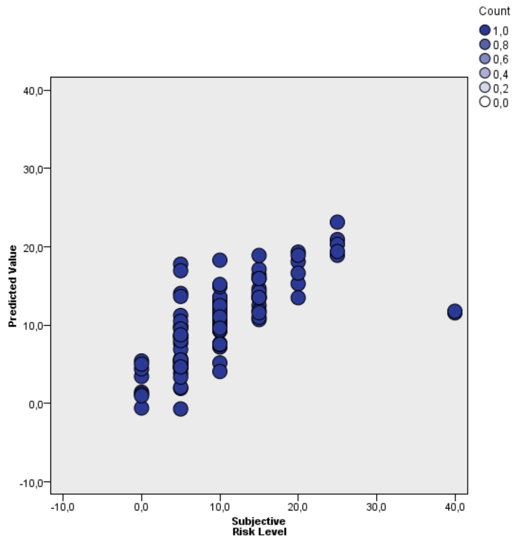
Random Intercept





All random parameters

No random parameters



Random intercept

Residual Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Var(RideNumber=0)	105,412	48,984	2,152	,031	42,398	262,080
Var(RideNumber=1)	108,571	50,250	2,161	,031	43,828	268,953
Var(RideNumber=2)	7,166	4,758	1,506	,132	1,950	26,329
Var(RideNumber=3)	27,950	14,565	1,919	,055	10,065	77,616
Var(RideNumber=4)	13,194	7,230	1,825	,068	4,507	38,623
Var(RideNumber=5)	12,918	7,105	1,818	,069	4,396	37,961
Var(RideNumber=6)	28,590	14,210	2,012	,044	10,793	75,733
Var(RideNumber=7)	12,816	7,344	1,745	,081	4,169	39,402
Var(RideNumber=8)	8,858	5,459	1,623	,105	2,647	29,642
Var(RideNumber=)	9,954	5,980	1,665	,096	3,066	32,312

Covariance Structure:Diagonal
Subject Specification:ParticipantNumber
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Random Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Variance	17,287	9,981	1,732	,083	5,576	53,600

Covariance Structure:Unstructured
Subject Specification:ParticipantNumber
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Figure 82: Random intercept variation per ride and per participant

Figure 83: GLMM for the Subjective Risk Level of overtaking scenarios

Target		Subjective Risk Level
Probability Distribution		Normal
Link Function		Identity
Information Criterion	Akaike Corrected	.[a]
	Bayesian	.

Information criteria are based on the -2 log likelihood (237,676) and are used to compare models. Models with smaller information criterion values fit better.

[a]Cannot be computed due to a numerical problem.

All random effects included

Target		Subjective Risk Level
Probability Distribution		Normal
Link Function		Identity
Information Criterion	Akaike Corrected	277,838
	Bayesian	278,585

Information criteria are based on the -2 log likelihood (241,172) and are used to compare models. Models with smaller information criterion values fit better.

Random parameter: mean distance to curb

Target		Subjective Risk Level
Probability Distribution		Normal
Link Function		Identity
Information Criterion	Akaike Corrected	217,132
	Bayesian	220,742

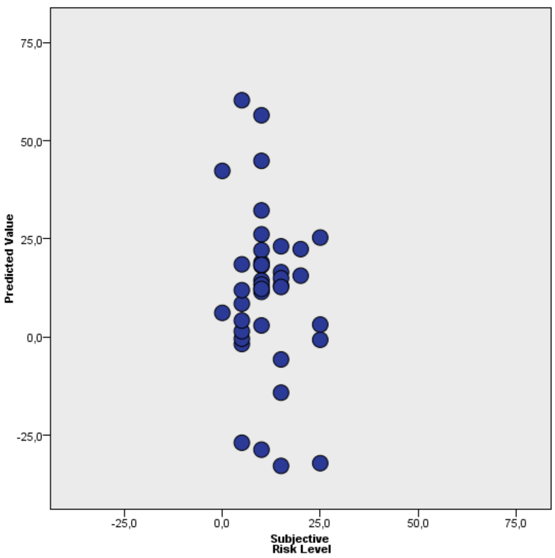
Information criteria are based on the -2 log likelihood (190,132) and are used to compare models. Models with smaller information criterion values fit better.

Random Intercept

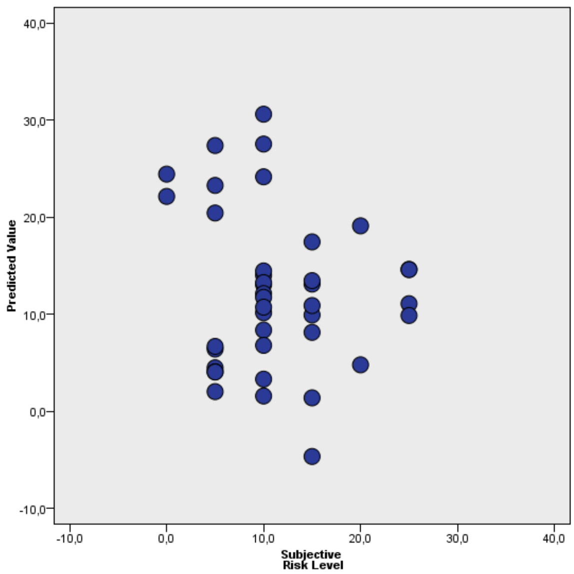
Target		Subjective Risk Level
Probability Distribution		Normal
Link Function		Identity
Information Criterion	Akaike Corrected	227,182
	Bayesian	231,535

Information criteria are based on the -2 log likelihood (204,325) and are used to compare models. Models with smaller information criterion values fit better.

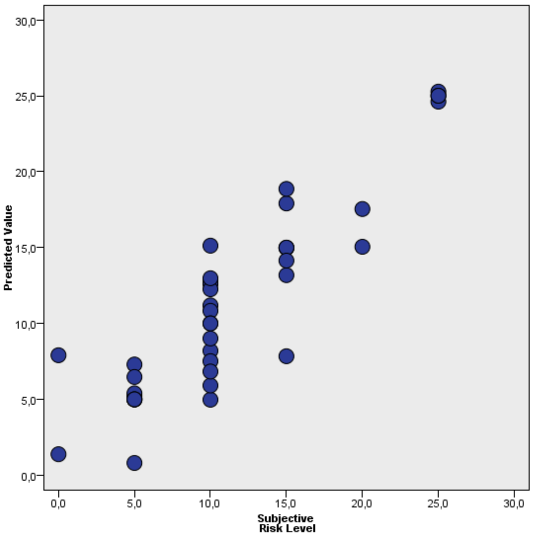
No random effect

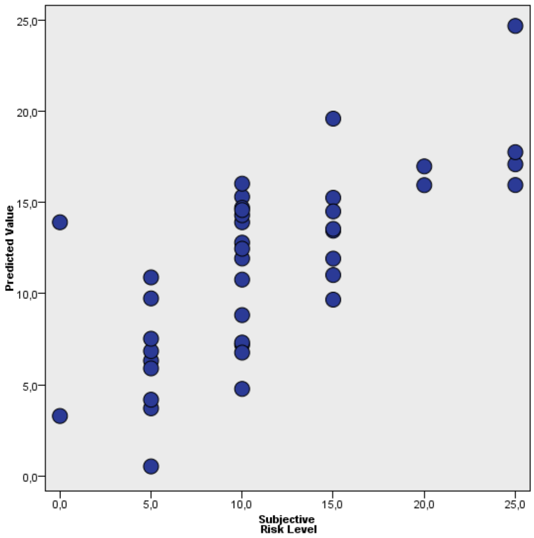


All random effects



Random – mean distance to curb





Random intercept　　　　No random effect

Residual Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Var(RideNumber=1)	15,636	23,979	0,652	,514	0,774	315,890
Var(RideNumber=2)	0,042	37,645	0,001	,999	0,000	.
Var(RideNumber=3)	16,523	21,565	0,766	,444	1,280	213,328
Var(RideNumber=4)	27,899	28,774	0,970	,332	3,696	210,615
Var(RideNumber=5)	4,713	13,764	0,342	,732	0,015	1 442,281
Var(RideNumber=6)	5,793[a]					
Var(RideNumber=7)	4,953[a]					
Var(RideNumber=8)	0,000	10,267	0,000	1,000	0,000	.

Covariance Structure:Diagonal
Subject Specification:ParticipantNumber
[a] This parameter is redundant.
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Random Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Variance	19,562	21,838	0,896	,370	2,194	174,448

Covariance Structure:Unstructured
Subject Specification:ParticipantNumber
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Figure 84: GLMM with random intercept

Figure 85: GLMM for the objective risk

Target		Objective Risk
Probability Distribution		Normal
Link Function		Identity
Information Criterion	**Akaike Corrected**	278 428,865
	Bayesian	279 580,723

Information criteria are based on the -2 log likelihood (277 946,744) and are used to compare models. Models with smaller information criterion values fit better.

All random

Target		Objective Risk
Probability Distribution		Normal
Link Function		Identity
Information Criterion	**Akaike Corrected**	14 605,200
	Bayesian	15 679,185

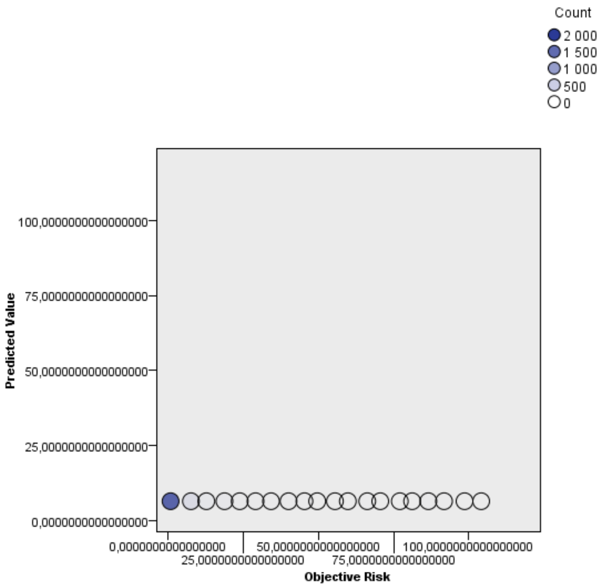
Information criteria are based on the -2 log likelihood (14 160,209) and are used to compare models. Models with smaller information criterion values fit better.

No random

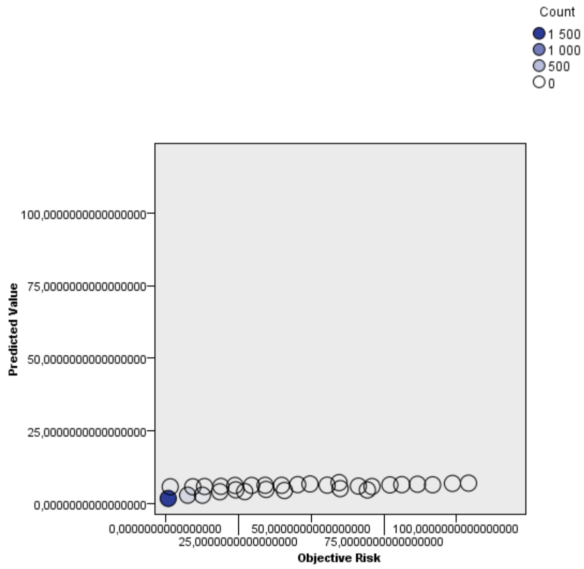
Target		Objective Risk
Probability Distribution		Normal
Link Function		Identity
Information Criterion	**Akaike Corrected**	14.433,864
	Bayesian	15.512,969

Information criteria are based on the -2 log likelihood (13.986,397) and are used to compare models. Models with smaller information criterion values fit better.

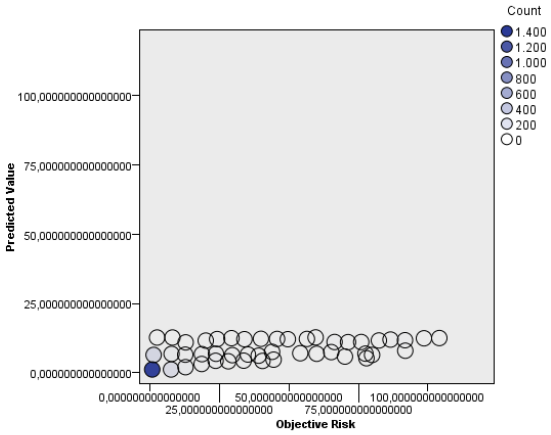
Random intercept



All random variables



No random variables



Random intercept

Random Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Variance	4,443	2,320	1,915	,055	1,597	12,363

Covariance Structure: Unstructured
Subject Specification: ParticipantNumber
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Figure 86: Random intercept variance per participant

Figure 87: GLMM for trust

Target		Trust
Probability Distribution		Normal
Link Function		Identity
Information Criterion	Akaike Corrected	115,354
	Bayesian	139,300

Information criteria are based on the -2 log likelihood (89,925) and are used to compare models. Models with smaller information criterion values fit better.

Random intercept

Target		Trust
Probability Distribution		Normal
Link Function		Identity
Information Criterion	Akaike Corrected	285,404
	Bayesian	326,985

Information criteria are based on the -2 log likelihood (214,769) and are used to compare models. Models with smaller information criterion values fit better.

All random parameters

Target		Trust
Probability Distribution		Normal
Link Function		Identity
Information Criterion	Akaike Corrected	119,911
	Bayesian	147,410

Information criteria are based on the -2 log likelihood (89,057) and are used to compare models. Models with smaller information criterion values fit better.

Subjective Risk as a random parameter

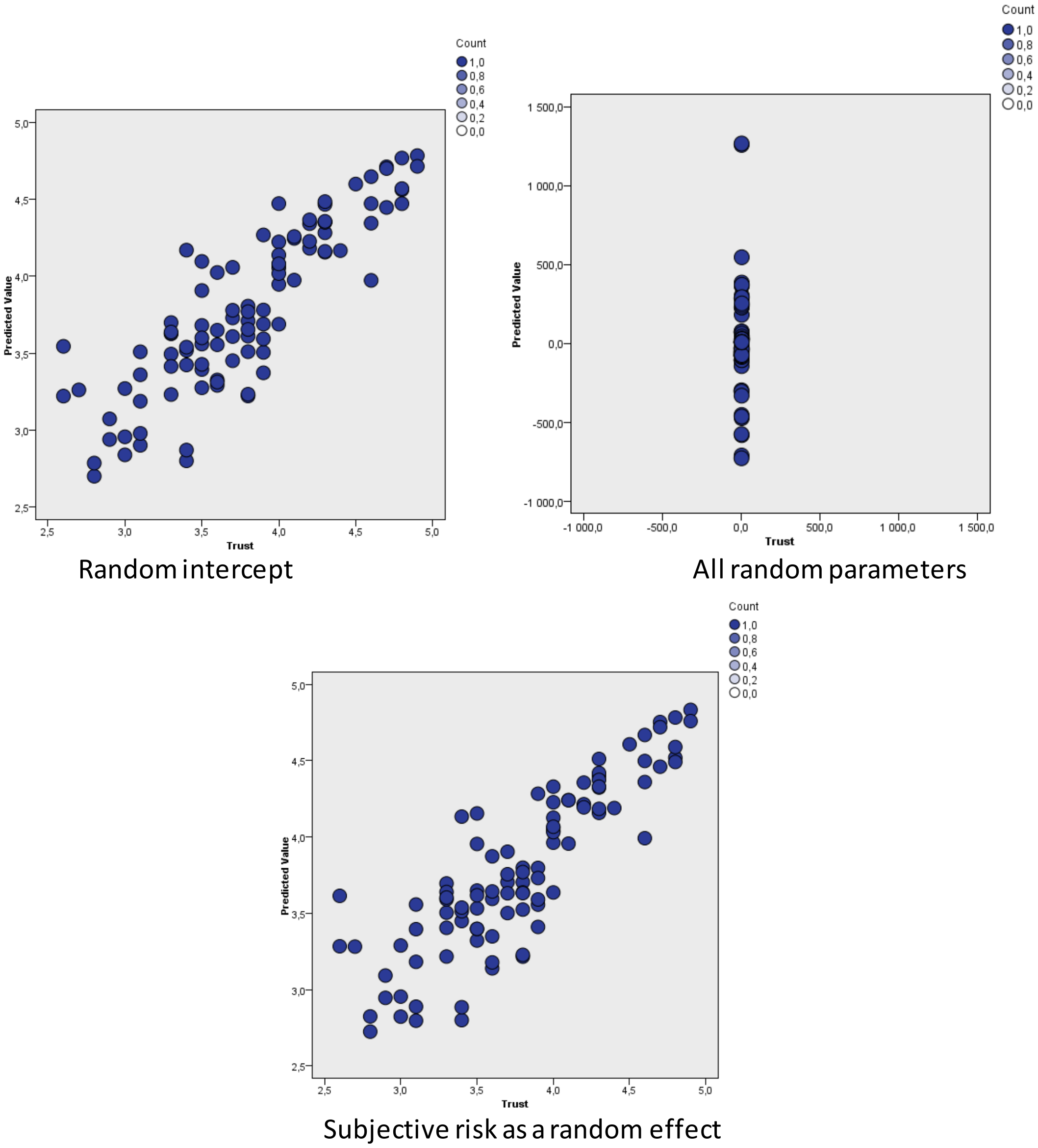


Figure 88: GLMM with a random intercept

Residual Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Var(RideNumber=0)	0,164	0,088	1,876	,061	0,058	0,467
Var(RideNumber=1)	0,219	0,107	2,057	,040	0,085	0,568
Var(RideNumber=2)	0,083	0,045	1,842	,065	0,029	0,241
Var(RideNumber=3)	0,102	0,055	1,853	,064	0,035	0,294
Var(RideNumber=4)	0,036	0,025	1,456	,145	0,009	0,139
Var(RideNumber=5)	0,051	0,029	1,791	,073	0,017	0,153
Var(RideNumber=6)	0,055	0,030	1,833	,067	0,019	0,159
Var(RideNumber=7)	0,123	0,063	1,965	,049	0,045	0,333
Var(RideNumber=8)	0,012	0,013	0,924	,355	0,001	0,101
Var(RideNumber=)	0,093	0,047	1,956	,050	0,034	0,253

Covariance Structure:Diagonal
Subject Specification:ParticipantNumber
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Random Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Variance	0,145	0,078	1,859	,063	0,051	0,416

Covariance Structure:Unstructured
Subject Specification:ParticipantNumber
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Random Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
UN (1,1)	0,001	5,938	0,000	1,000	0,000	.
UN (2,1)	-0,013	0,410	-0,031	,976	-0,816	0,791
UN (2,2)	0,072	0,013	5,502	,000	0,051	0,103
UN (3,1)	0,000	0,172	0,002	,998	-0,336	0,337
UN (3,2)	-0,000[a]					
UN (3,3)	0,072[a]					
UN (4,1)	-0,085	2,070	-0,041	,967	-4,143	3,972
UN (4,2)	0,013	0,303	0,042	,967	-0,581	0,607
UN (4,3)	-0,000	0,215	-0,002	,998	-0,423	0,422
UN (4,4)	0,196	3,574	0,055	,956	0,000	641 805 691 915 729,000
UN (5,1)	0,054	0,987	0,055	,956	-1,880	1,988
UN (5,2)	-0,000[a]					
UN (5,3)	-0,000[a]					
UN (5,4)	-0,003	1,233	-0,003	,998	-2,420	2,414
UN (5,5)	0,051[a]					

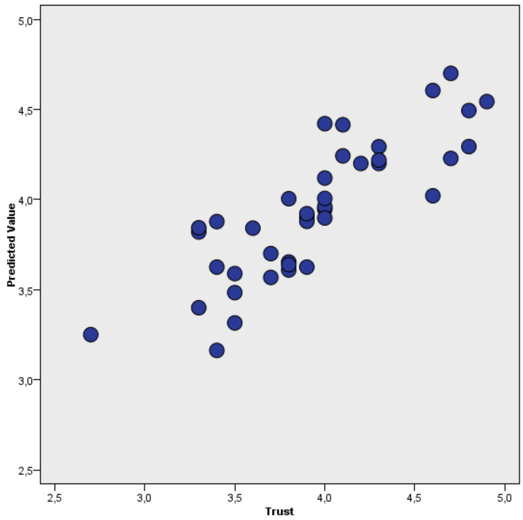
Covariance Structure:Unstructured
Subject Specification:ParticipantNumber
[a]This parameter is redundant.

Figure 89:The random parameter table for the GLMM with all random parameters included

Figure 90: GLMM for trust for the overtakings

Target		Trust
Probability Distribution		Normal
Link Function		Identity
Information Criterion	**Akaike Corrected**	80,705
	Bayesian	84,316

Information criteria are based on the -2 log likelihood (53,705) and are used to compare models. Models with smaller information criterion values fit better.



Residual Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Var(RideNumber=1)	0,029	0,069	0,419	,676	0,000	3,121
Var(RideNumber=2)	0,171	0,140	1,225	,221	0,035	0,848
Var(RideNumber=3)	0,163	0,114	1,426	,154	0,041	0,644
Var(RideNumber=4)	0,176	0,214	0,824	,410	0,016	1,899
Var(RideNumber=5)	0,000[a]					
Var(RideNumber=6)	0,077	0,078	0,992	,321	0,011	0,557
Var(RideNumber=7)	0,078	0,192	0,408	,683	0,001	9,514
Var(RideNumber=8)	0,110[a]					

Covariance Structure:Diagonal
Subject Specification:ParticipantNumber
[a]This parameter is redundant.
The covariance structure is changed to Scaled Identity because the random effect has only one level.

Random Effect	Estimate	Std.Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Variance	0,083	0,068	1,216	,224	0,017	0,417

Covariance Structure:Unstructured
Subject Specification:ParticipantNumber
The covariance structure is changed to Scaled Identity because the random effect has only one level.

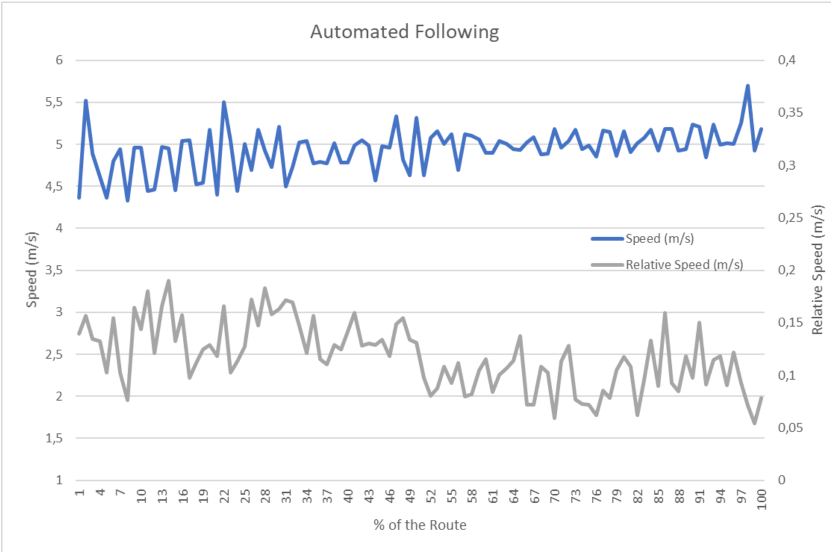


Figure 91: Speed, relative speed along the route for automated following

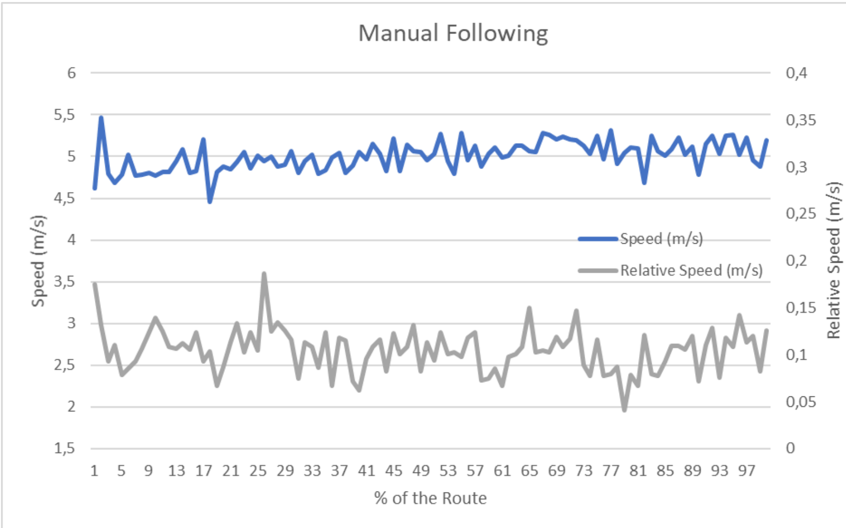


Figure 92: Speed, relative speed along the route for manual following

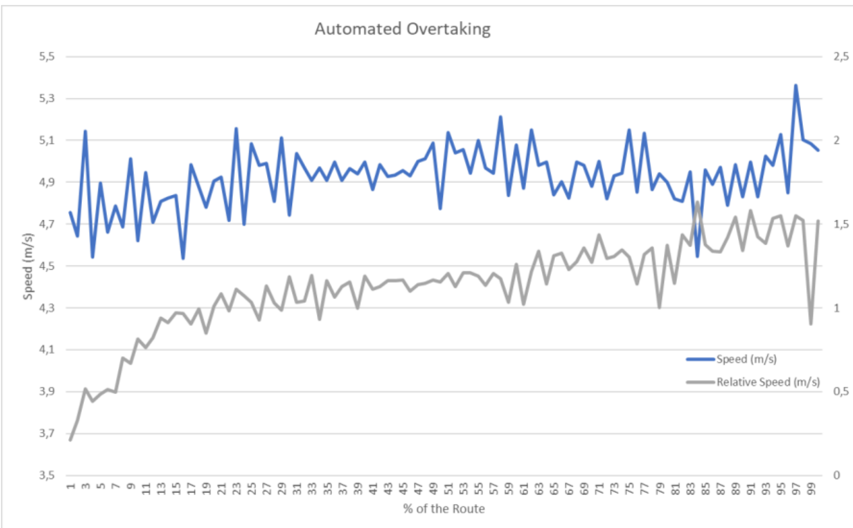


Figure 93: Speed, relative speed along the route for automated overtaking

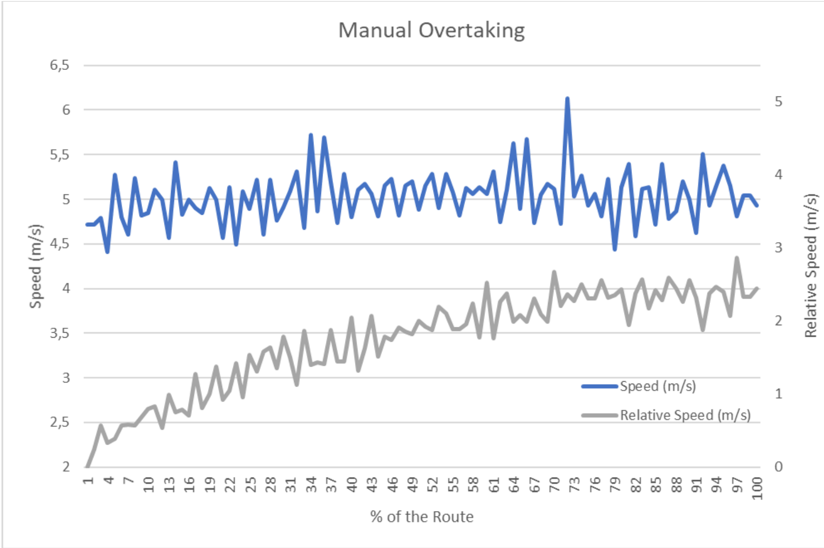


Figure 94: Speed, Relative speed along the route for manual overtaking

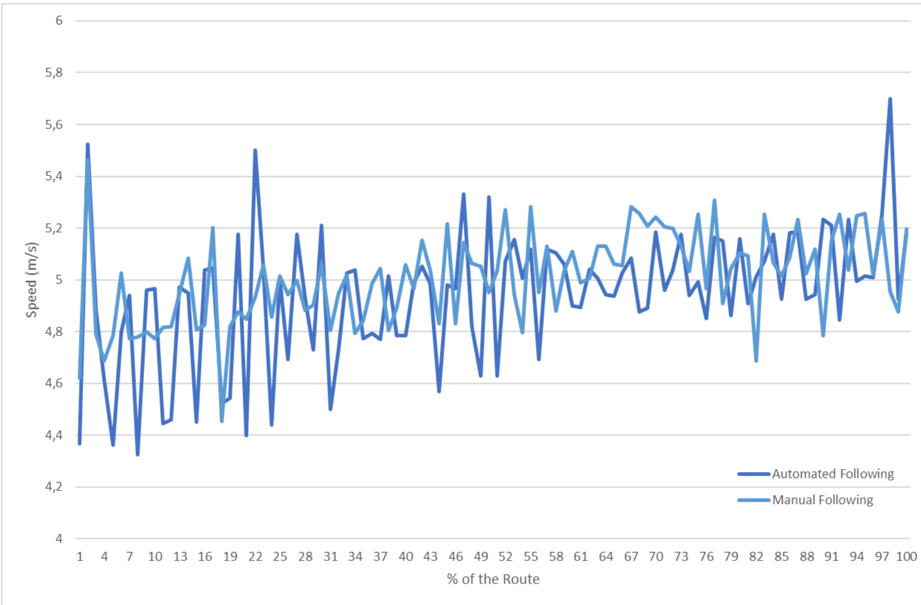


Figure 95: Speed along the route for followings

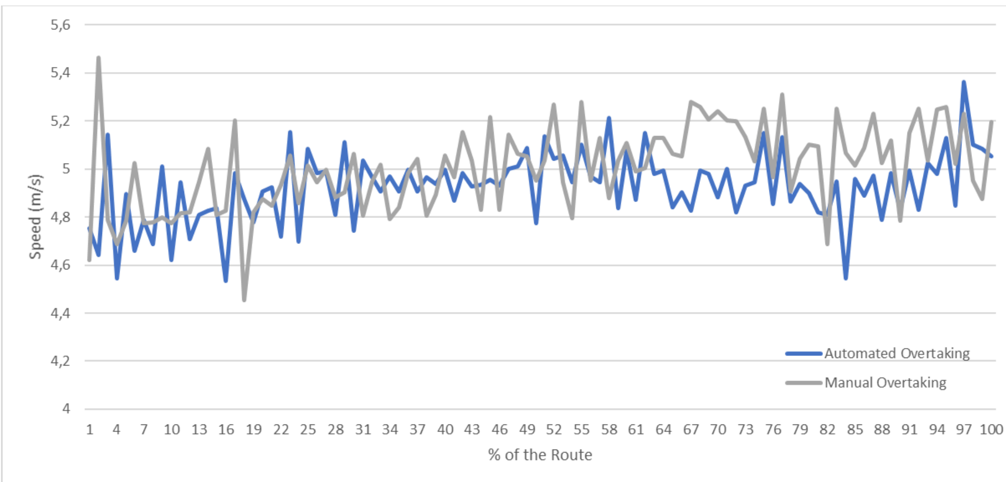


Figure 96: Speed along the route for overtakings

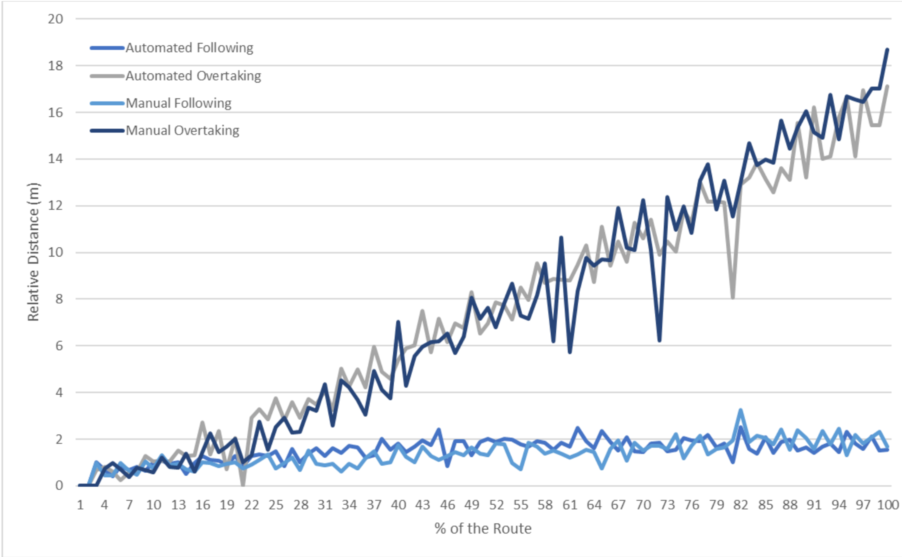


Figure 97: Relative distance along the route

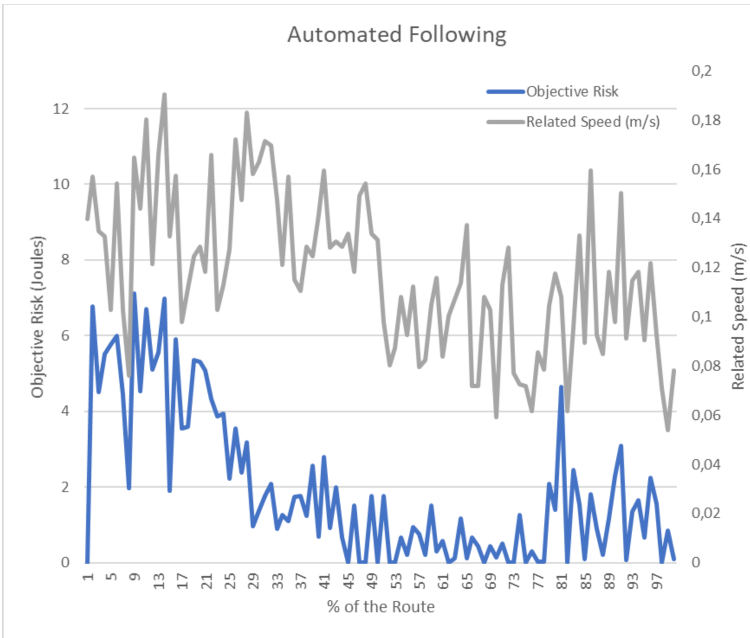


Figure 98: Objective risk, relative speed along the route for automated following

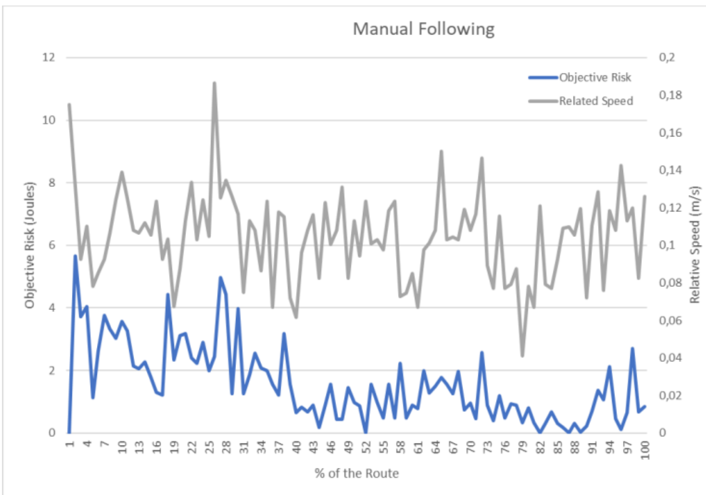


Figure 99: Objective risk, relative speed along the route for manual following

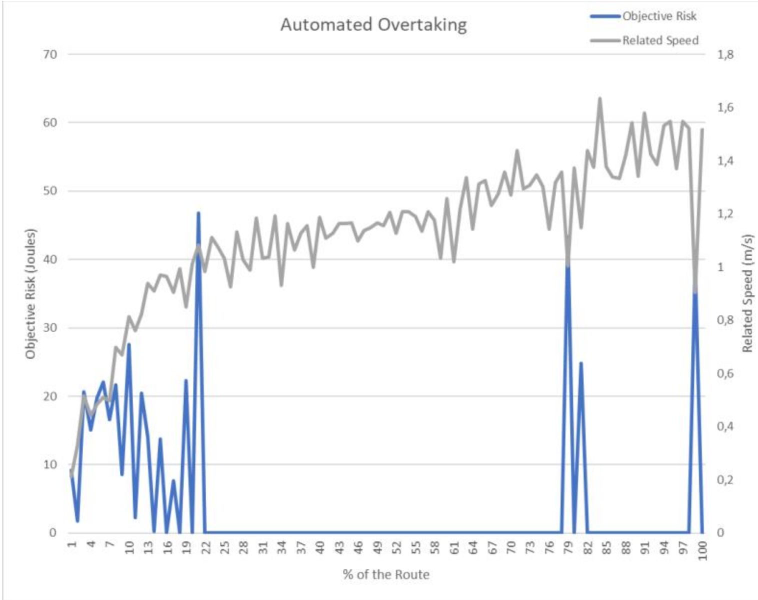


Figure 100: Objective risk, relative speed along the route for automated overtaking

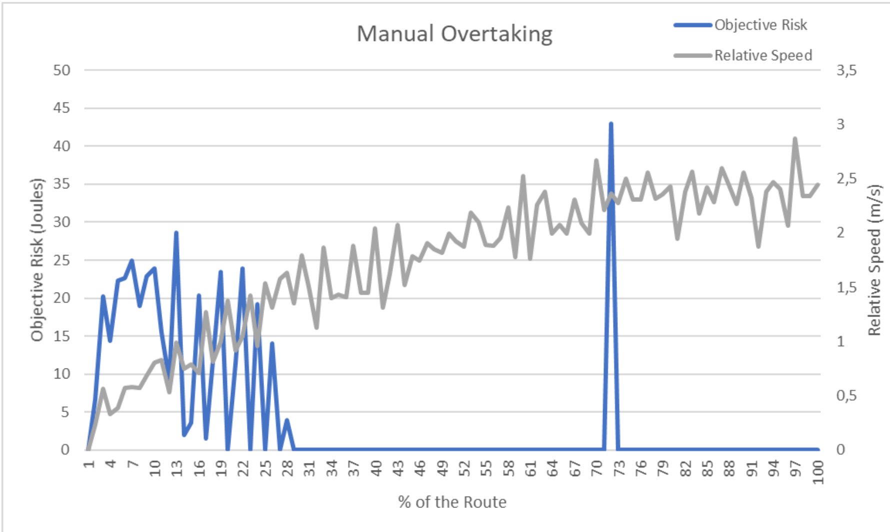


Figure 101: Objective risk, relative speed along the route for manual overtaking