Perceived risk of interaction with e-bikes

by

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Preface

"Life is constantly uncertain about what to do."

I am writing to express my deepest gratitude as I approach the culmination of my master's program. Reflecting on this journey, I realize how much I have grown and learned, both academically and personally.

When I first arrived in the Netherlands two years ago, I confess I was not as prepared as I should have been. The experience was overwhelming, filled with new challenges and unforeseen efforts. Over time, I conquered numerous hurdles in my studies and daily life. Right now, I am immensely proud to obtain my master's degree from TU Delft.

This pursuit of a Master's degree has been a truly enriching experience. I have acquired invaluable skills in academic research and gained extensive knowledge in the field of traffic and planning. Most significantly, the process of completing my master's thesis has fortified my resilience and confidence, assets I believe will serve me well in the future.

I am deeply grateful to my esteemed supervisors. Dr. Amir Pooyan Afghari, his unwavering guidance, and weekly feedback were instrumental in realizing this thesis. Dr. Haneen Farah, her patient mentorship in research methods and insightful perspectives greatly enhanced my work. Dr. Sina Nordhoff, her expertise in survey methodology and passion for research inspired me throughout. I am also grateful to Dr. Khashayar Kazemzadeh, recommended by Dr. Amir Pooyan Afghari, for providing invaluable feedback on my survey design.

I must extend my thanks to those who supported me through this thesis. My dedicated volunteer, Zhengliang Duanmu, assisted me with the e-bike trials and participated in the video recordings. To all the participants in my survey, your contributions were invaluable; this work would not have been possible without your input. Lastly, I want to express my deepest gratitude to my family and friends. Your unwavering love and support mean the world to me.

It is an immense honor to have completed my Master's degree, and I am deeply grateful for the courage and confidence you all have instilled in me to embrace what the future holds.

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Summary

E-bikes have gained global popularity due to their environmentally friendly and sustainable attributes, as well as their ability to provide fast speeds and power assistance. However, the increasing popularity of e-bikes has introduced conflicts and crashes with other road users, especially the interaction with conventional bikes, as e-bikes and bikes share the same cycling infrastructure. To study the perceived risk of interaction with e-bikes, this research delves into the various factors, in terms of traffic environment, bicycle type, and individual factors.
This research has used the video-based survey method to measure the perceived risk of cyclists and presented traffic environment and bicycle types in hypothetical traffic scenarios with pre-recorded videos. A questionnaire is designed to investigate participants‘ perceived risk of hypothetical bicycle interactions and their personal information on demographics, cycling experience, competence of riding skills, cycling behaviors, and expectancy on e-bikes. Moreover, the perceived risk is measured by two items separately: the rate of perceived risk and the likelihood of being involved in a crash. After recruitment and data collection, the effects of various factors have been estimated by the random-effects ordered logit model.
Results implied that compared to interaction between conventional bikes, riding on an e-bike when encountering a conventional bike decreased the perceived risk. Moreover, riding at peak hours and having a conflict with left-turning cyclists was found to increase the perceived risk, while riding at a large intersection was found to decrease the perceived risk. In terms of individual factors, the experience of bicycle crashes and the preference to use an e-bike were found positively related to the perceived risk. While the competence of cycling skills and age were found negatively associated with perceived risk. Additionally, it was found that traffic environment factors were more prominent in predicting the rate of perceived risk, while individual factors had a stronger influence on predicting the likelihood of being involved in a crash.
These findings provide insights into the influence of e-bikes in shared cycling spaces, underscore the importance of traffic management and safety measures in crowded bicycle traffic, and emphasize the significance of intervention and educational initiatives for cyclists to decrease the perceived risk and enhance cycling safety.

Keywords: Interaction with e-bike; Perceived risk; Cycling safety; Video-based survey

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1 Introduction

1.1. Background

The expansion of road traffic caused various environmental challenges linked to conventional fossil-fueled vehicles, such as their reliance on fossil fuels and the associated greenhouse gas emissions. To address these concerns, European countries had aimed at the transition of sustainable mobility, with the electrification of vehicles as one of the goals. As part of this shift towards sustainable mobility, in recent years, the E-bike has become an emerging transport option that brings environment, mobility, and health benefits(Simsekoglu & Klöckner, 2019). An E-bike is a motorized bicycle with an integrated electric motor used to assist propulsion. In European standards, it is referred to as an "Electrically Power Assisted Cycle (EPAC)". The electric motor provides assistance while pedaling, making it easier to ride uphill or against strong winds, and providing the possibility to ride in longer distances. The less effort cost of cycling and the environmentally friendly and sustainable features have led to e-bikes' widespread popularity. As a result, e-bike sales have been rapidly increasing in Europe in the last decades, from 0.7 million in 2010 to 5.06 million in 2021 (RAI). Such a prevalence is also reflected in the usage of e-bikes. In 2020, more than a quarter of the total cycling distance traveled was done by electric bicycle in the Netherlands (SWOV, 2022).

As a country having more bicycles than people, the Netherlands has biking rooted in its culture, with around 1 million bicycles being sold every year. Meanwhile, e-bike usage increased over the years in the Netherlands. SWOV reported that there were 2.9 million electric bikes in 2022, which was more than 12% of the total number of bicycles in the Netherlands. And the

cycling kilometers on an e-bike increased in the 12-50 age group of cyclists(SWOV, 2022).
The prevalence of cycling in the Netherlands also brings prevalence in bicycle accidents. Statistics Netherlands (CBS) reported that in 2022, almost 40% of traffic accident casualties were cyclists, which is the highest number of cycling deaths since 1996 when registration started(Netherlands, 2023).
Moreover, the popularity of e-bikes causes some serious concerns for safety. SWOV reported that the most serious road injuries were cyclists in 2020, though it was not possible to distinguish which type of bicycle they used(SWOV, 2022). One research in trauma center in Switzerland showed that almost 1/3 of patients with bicycle-related injuries were using an e-bike(Berk et al., 2022).In 2019 and 2020, almost one in three fatal bicycle victims rode an electric bicycle in the Netherlands(SWOV, 2022). E-bike accidents are more frequent and severe due to their higher speed and greater mass than conventional bikes(Dozza, Bianchi Piccinini, et al., 2016). The proportion of e-bike injuries increased in the Netherlands between 2012 and 2016, and e-bike accidents have higher injury severity scores compared to conventional bike (Verstappen et al., 2021). The e-bike can easily reach a maximum speed of 25km/h with power assistance, which is faster than the conventional bike. And naturalistic experiments have shown that e-bikes are significantly faster than conventional bikes in both urban areas and rural areas(Twisk et al., 2021). Compared to cyclists on conventional bikes, e-bike riders have a shorter response time to take action to prevent or mitigate accidents. Moreover, with a similar appearance, it is hard to distinguish between a conventional bike and an e-bike from a distance. The failure to distinguish a conventional bike and an e-bike may cause potential danger, for e-bikes the actual time gap between the conflicts is shorter than expected by other road users (vehicles, bikes, pedestrians, etc.) due to the higher speed of e-bikes, which would lead to conflicts or even accidents eventually (Dozza, Bianchi Piccinini, et al., 2016). In addition, the battery to assist pedal power makes the e-bike heavier than a conventional bike, while the greater mass would also result in serious injuries in critical incidents.

Because of the kinematic and mass characteristics of the e-bike, e-bike users exhibit dual behaviors, where they can be vulnerable road users facing the risk of severe injuries in certain situations, while in other cases, they may bring a threat to other vulnerable road users. On the one hand, due to lack of protection and exposure to the traffic environment, when it comes to an accident with motor vehicles, e-bike users act as vulnerable road users who would take more and more severe damage. On the other hand, they have the potential to bring damage to vulnerable road users, as the motorized characteristics (for example, fast speed and acceleration) of e-bikes may cause conflicts or accidents with conventional bikes or pedestrians.

Despite the different characteristics in terms of speed, power assistance, and weight between bikes and e-bikes, in the Netherlands they are regulated to use the same cycling infrastructure, where conflicts, near-crashes, and even crashes occur frequently between conventional bikes and e-bikes. Therefore, the study on the risk of interaction between e-bikes and conventional bikes deserves further exploration. A study by Vlakveld et al. (2021) revealed that the probability of conflicts was higher when bikes were in the proximity of e-bikes and occurred when e-bikes used bicycle facilities. Though several studies have compared the discrepancy of riding behaviors between bikes and e-bikes(Dozza, Bianchi Piccinini, et al., 2016; Petzoldt et al., 2017; Schleinitz et al., 2017; Twisk et al., 2021), the risk of interaction between bikes and e-bikes is less explored. The growing popularity of e-bikes has led to conflicts and crashes with conventional bikes and other road users. One of the most risky and critical incidents for cyclists is when they approach intersections and interact with other road users, including vehicles, other cyclists, and pedestrians(Dozza & Werneke, 2014).

In order to investigate the risk of bike interactions, it is crucial to understand both the actual risk and the perceived risk associated with cycling accidents and the factors influencing them. This research firstly focuses on the perceived risk as it interconnects and influences actual risk. Research has shown that higher subjective risk perception leads to decreased risky behavior and a lower number of self-reported bicycle crashes(Useche et al., 2019). As illustrated in Fig1.1, the occurrence of bicycle accidents or actual risk raises cyclists' perception of risk, prompting them to pay more attention to their riding behaviors and mitigate actual risks and consequences. However, on the other hand, both the underestimation and overestimation of perceived risk can increase or decrease the actual risk(Chaurand & Delhomme, 2013). For instance, when cyclists underestimate the risk of cycling and perform risky cycling behaviors, they may more easily be involved in a crash or have more severe injuries. When cyclists overestimate the risk of cycling and thus take more mental stress, it may decrease or increase the probability of being involved in a crash.

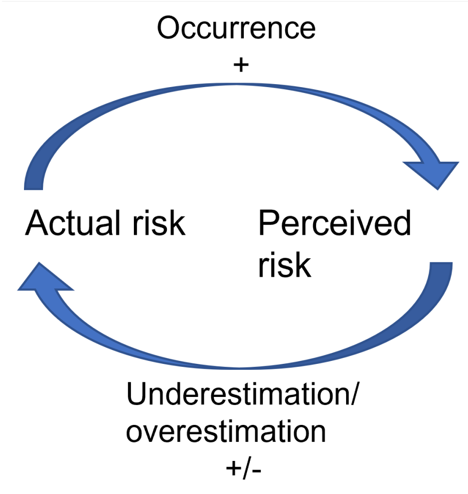

Figure 1.1: Relationship between actual risk and perceived risk

Currently, most studies use naturalistic data to analyze and compare crashes between bikes and e-bikes (Dozza, Bianchi Piccinini, et al., 2016; Panwinkler & Holz-Rau, 2021; Vlakveld et al., 2021), while the information recorded from actual crash data was often too small to reflect cycling behaviors. However, perceived risk can provide more information from the perspective of psychology, emotion, attitudes, and personal experience to help with a deeper understanding of bicycle crashes. Moreover, the perceived risk and anticipation of crashes in the cycling situation shape cyclists' riding decisions and actions to mitigate and manage cycling risks. For instance, Yao and Wu (2012) studied the risk perception of e-bike riders in China and explored the relationship between risk perception, traffic safety attitudes, and aberrant riding behaviors. The results revealed that a high perception of risk was associated with positive attitudes toward traffic safety and less likelihood to commit aberrant riding behaviors. By understanding the perceived risk of cycling, we can gain insights into how individuals' perception of risks affects their decision-making processes, actions, and overall performance in dynamic cycling situations.

In risk perception studies, the traffic scenarios are presented in different ways: textual description(Chaurand & Delhomme, 2013), images, pre-recorded videos(Lehtonen et al., 2016; Liu et al., 2020), bicycle simulator(Nazemi et al., 2021), and field experiment(Fitch & Handy, 2018). The textual description is the easiest way to present the traffic scenarios and can be widely distributed to a great number of respondents. However, most of the time the textual description is hard to understand and respondents may find difficulty in imagining the traffic scenarios. Compared to textual description, traffic scenarios shown in images and videos are easier to understand and give respondents a feeling of reality. Meanwhile, via online platforms, both the images and videos can be distributed widely and recruit a great group of participants. On the other hand, though the bicycle simulator method and field experiment method can definitely provide the traffic scenarios most closely to reality, the issue is the small sample of participants. It is much harder to reach a large group of people to participate in the experiment, therefore bias from a sample of participants would occur. Eventually in order to present realistic scenarios of bike interaction with well-controlled stimuli, this research used pre-recorded videos filmed from first-person cyclist's view and combined with several questions to investigate the perceived risk of cyclists in specific bike interaction scenarios.

1.2. Outline

The outline of the thesis report is organized as follows:

- Chapter1 introduces the background of the research and the outline of the report.
- Chapter2 conducts the literature review and summarizes the hypotheses, addresses the research gap, research objective, and questions.
- Chapter3 explains the methodology adopted in the research, first introducing the conceptual framework and research design, then explaining the procedure to set traffic scenarios, the video-based survey design, and the data analysis method.
- Chapter4 analyses the survey data, presents the corresponding results, and interprets the model with discussion.
- Chapter5 presents the conclusion of the research and reflects to limitations.

2

Literature review

2.1. Factors contributing to bike and e-bike crashes

In order to gain more insights into the safety issues of bikes and e-bikes, and to have a deeper comprehension of bike and e-bike crashes, many researchers have investigated bike and e-bike accidents in terms of traffic environment and speed. Moreover, to compare the safety issues between bikes and e-bikes, many studies have investigated bike types involved in bicycle conflicts and crashes and analyzed variations in cycling behavior.

2.1.1. Traffic environment

Infrastructure:

The quality of infrastructure plays a critical role in the riding experience. Factors such as road conditions, presence of bike lanes, signage, and the separation of cyclists from motorized traffic were found related to bicycle accidents (Petzoldt et al., 2017). Naturalistic cycling data indicated that riding on poorly maintained road surfaces significantly increased the risk of experiencing critical events (Dozza & Werneke, 2014). And the slippery road surface was one of the most often crash causes of e-bike single accidents (Hertach et al., 2018).

Intersection:

The characteristics of the road, such as the presence of intersections, roundabouts, curves, or narrow lanes, can influence cyclists' safety (Dozza & Werneke, 2014). These characteristics and different riding facilities provide various elements of the riding environment. As one of the most complex riding facilities, the intersection composes traffic from different directions,

signals, and guidance, and conflicts with other road users, which increases the complexity, stress, and mental workload of cyclists.
The research by Petzoldt et al. (2017) confirmed that at intersections the risk of being involved in a conflict was twice as high for e-bikes. A study by Dozza and Werneke (2014) revealed that approaching an intersection increased the risk of experiencing dangerous traffic encounters. The naturalistic study by Vlakveld et al. (2021) indicates that one of the most common conflicts was e-bikes not yielding to bikes at intersections. Several studies have found that riding at unsignalized intersections was one of the most risky incidents for bikes and e-bikes. A study by Deliali et al. (2021) indicated that one-third of crashes involving bikes and e-bikes occurred at urban intersections, most of which were unsignalized intersections. More specifically, Bai et al. (2013) analyzed bicycle conflicts through videos collected from a signalized intersection, and the results showed that among 16 types of conflicts at a 4-leg intersection, more than half of the conflicts (56.6%) were left-turn vehicle with cross e-bikes and bikes, and 19.8% conflicts were right-turn vehicle with cross e-bikes and bikes. Besides the conflict type, the distance between other road users impacted the crash risk, as Vlakveld et al. (2021) found that high crash risk of the bicycle was associated with the proximity of the bicycles and e-bikes, and conflicts more frequently occurred in crossing maneuvers and at intersections.

The intersection is one of the critical locations where bicycle conflicts and crashes occur more frequently, compared to bike path sections. Moreover, at intersections, the likelihood of e-bikes being involved in crashes was higher than conventional bikes (Petzoldt et al., 2017). In this research, the intersection type will be further looked into to examine the effect on the perceived risk of bike interactions. As the high crash risk associated with the proximity of the bicycles and e-bikes (Vlakveld et al., 2021), it is expected that at small intersections cyclists would perceive a higher level of risk than at large intersections because small intersections forced cyclists to be closer with each other, the change to have collision would be higher. Therefore this research compares the intersections with different sizes, and consequently, the hypothesis is formulated as:

- The perceived risk of cyclists will be higher at small intersections.

Other road users and traffic volume:

Several studies revealed the participation of other road users would increase the crash risk for bikes and e-bikes. By analyzing data collected from naturalistic riding experiences, Dozza and Werneke (2014) proved that the involvement and interruption of other road users (such as other bicyclists or pedestrians) provided more threats in critical events of bicycles. Another similar naturalistic study by Petzoldt et al. (2017) revealed that other road users participating in or crossing the bike path caused conflicts for both conventional bicycles and electric bicycles. The crash partners of bikes and e-bikes were identified by Vlakveld et al. (2021), and the naturalistic observation revealed that bicycles were the most frequent potential crash partners of e-bikes. Besides the interaction with other road users, traffic volume indicated the number of other road users encountering, which also impacted the crash risk of bicycles. Pejhan et al. (2021) had conducted naturalistic research on e-bike riding and suggested that dense traffic and the demand of riding in complex traffic conditions would result in higher mental workload, consequently causing crashes.

The traffic volume of bicycles is one of the factors that contribute to the complexity of riding. As discussed in section 2.2.1, participation of other road users increased the risk of being involved in bicycle crashes, and high traffic volume indicated a higher probability of having conflicts with other road users. Additionally, high traffic volume leads to the demand for riding in complex environments, which impacts cyclists‘ risk perception of riding. It is expected that higher traffic volume would induce a higher level of perceived risk by increasing the mental workload of cyclists. Consequently, the hypothesis is formulated as follows:
- Higher traffic volumes of bicycle leads to higher perceived risk of cyclists.

2.1.2. Cycling speed

Through naturalistic observation and empirical data, the majority of investigations into bike and e-bike accidents have consistently highlighted that the high speed of cycling is one of the most significant factors contributing to crashes or conflicts of bikes and e-bikes. Dozza, Bianchi Piccinini, et al. (2016) used naturalistic data collected from 12 e-cyclists with 88 critical events (crashes and near-crashes) to understand the crash causation. By analyzing odds ratios, results showed that speed had the highest influence on critical events occurrence. Haustein and Møller (2016) used the data from an internet survey of 685 users in Denmark to analyze the factors affecting perceived e-bike safety and the involvement of incidents. Through linear regression, the results showed that other road users underestimating the speed of e-bikes is the most frequent cause of safety-critical incidents. Hertach et al. (2018) used self-reported information to investigate the characteristics of single-vehicle accidents with e-bikes in road traffic. Within a total of 3658 respondents, 638 e-bike users (17%) reported single-vehicle accidents, and the data showed that skidding due to an icy or wet street were the most important accident mechanisms, and the slippery road surface, riding too fast and inability to keep the balance were the most often crash causes. Panwinkler and Holz-Rau (2021) analyzed 1738 free text descriptions written by police officers on site to study the specific causes of pedelec single accidents. Through ordered probit analysis, new categories of accident causes were developed as well as analyzing the severity of injuries, and results indicated that too fast speed, indication of alcohol, and downhill slope were the most frequently mentioned causes of severe injuries in pedelec single accidents.

2.1.3. Bicycle type

Numerous studies have compared bikes and e-bikes by cycling characteristics, with certain research also focusing on comparative analyses of crash involvement between these two bike categories.

Huertas-Leyva et al. (2018) investigated the change in cycling behaviors of six cyclists first riding conventional bikes and then switching to riding an e-bike. The kinematic changes were found that all participants rode faster on an e-bike by 2.9-5.0km/h than on a conventional bike. The cycling behaviors of hard braking unexpectedly and sharp deceleration were found increasingly performed when riding an e-bike, where the risk of braking hard was also higher on an e-bike. Moreover, the pattern of interacting with other road users was found different when switching from riding a conventional bike to an e-bike, as a result of high speed, cyclists on e-bikes had less time to predict and react to the movements so to take sharp deceleration. Petzoldt et al. (2017) found that e-bikes were significantly faster than conventional bikes in naturalistic cycling observation, while no difference was found between e-bikes and bikes in the involvement of conflicts. The exception was the intersection where the risk of being involved in a conflict was twice as high for e-bikes. Schleinitz et al. (2017) had done an experiment on both conventional cyclists and pedelec users. The naturalistic data collected from 90 participants reflected that e-bikes would reach higher speeds than conventional bikes. Dozza, Bianchi Piccinini, et al. (2016) had done experiments both on e-bikes and conventional bikes to conclude that e-bikes had more conflicts with motorized vehicles than conventional bikes did. Twisk et al. (2021) studied the speed characteristics of speed pedelecs, pedelecs, and conventional bicycles. The results reflected that speed-pedelecs are 10.4 km/h and 13.2 km/h faster than conventional bicycles in urban areas and rural areas respectively, however, no significant difference in the speed variation was found between pedelecs and conventional bikes.

Bicycle type is a particularly intriguing factor to explore. This factor holds significant interest because e-bikes correlate with both traffic environment and individual factors, thereby indirectly impacting the perceived risk. Sharing the same cycling facilities, however, conventional bikes and e-bikes have different characteristics, especially the speed, power assistance, and weight. Several research had compared kinematic characteristics between bike and e-bike and concluded that cyclists rode faster on an e-bike than conventional bike (Petzoldt et al., 2017; Schleinitz et al., 2017), where high speed is one of the critical causes of bike and e-bike crashes (Dozza, Bianchi Piccinini, et al., 2016; Haustein & Møller, 2016; Hertach et al., 2018; Panwinkler & Holz-Rau, 2021). Therefore this research further looked into the impacts of bike type in road interactions.

It is expected that encountering e-bikes would increase the perceived risk of cyclists who ride a conventional bike because e-bike has fast speed and acceleration and heavy weight, which may cause damage to vulnerable road users (riders of conventional bike). However, due to the same reason of e-bike kinematic characteristics, e-bike riders would perceive less risk, because riding on an e-bike provides more dominance in interaction with conventional bikes, and makes e-bike riders feel less vulnerable. Consequently, the hypothesis is formulated as follows:

- Encountering an e-bike would cause a higher risk perception than encountering a conventional bike.

- Riding on an e-bike and interacting with conventional bikes would cause less risk perception than riding on a conventional bike.

2.2. Perceived risk of cycling

Despite there being many studies looking into bicycle conflicts, crashes, and cycling behaviors of bikes and e-bikes using naturalistic data, the crash data was insufficient to comprehensively depict the correlation between crash risks and contributing factors. Many other studies have focused on the perceived risk of cycling and explored cycling safety issues from subjective evaluation. Three perspectives of individual factors, bias between perceived risk and actual risk, and methodology to assess risk perception had been reviewed.

2.2.1. Individual factors underlying perceived risk

Several individual factors were explored in association with the perceived risk or perceived safety of using bikes and e-bikes, in terms of demographics, experience, cycling behaviors, competence of riding skills, and expectancy on e-bike safety.

Demographics:

The study on self-reported cycling behavior concluded significant differences in traffic violation according to age and gender (Useche et al., 2018), where the results showed that males reported higher scores on violations and lower scores on positive behaviors, and the older group reported lower scores on violations and errors and higher scores on positive behaviors. A study by Haustein and Møller (2016) indicated that age and female gender are negatively associated with the perceived safety of e-bikes.

The old age group and female gender had been found associated with a low perceived risk of cycling, therefore the hypotheses are formulated as follows:

- The older group would perceive higher risk than the younger group.

- Females would perceive higher risk than males.

Experience:

The usage of bicycles impacted the perceived risk of cycling. Washington et al. (2012) reported that increased exposure by riding more days in a week is associated with a reduction of cyclists‘ perceived risk. Similarly Haustein and Møller (2016) reflected longer daily distance on an e-bike had a greater perceived safety, though they found that high cycling frequency was associated with high incident involvement.

The high usage of bikes and e-bikes was found related to less risk perception. The hypothesis is formulated as follows:

- Experienced cyclists who frequently use bikes or e-bikes are more likely to perceive less level of risk, in contrast to inexperienced cyclists who seldom ride a bike or an e-bike.

Moreover, cyclists' perception of risk is influenced by their experiences with bicycle crashes, as revealed in a study conducted by Schepers et al. (2020). The research indicated that cyclists who had encountered specific types of crashes were more likely to perceive higher risks associated with those particular crash types. In other words, if a cyclist had been involved in a certain kind of bicycle crash, they would be more likely to view that specific crash type as being riskier compared to other types of crashes. Therefore, personal experiences with crashes may shape cyclists' perception of risk and influence how they evaluate the potential dangers associated with different types of bicycle accidents.

The bike crash experience was found related to high-risk perception, therefore the hypothesis is formulated as follows:

- Cyclists who have been involved in crashes with bikes or e-bikes tend to perceive a higher level of risk, compared to cyclists without crash involvement.

Expectancy on e-bike safety:

Haustein and Møller (2016) studied e-bike safety issues from two perspectives: perceived safety and incident involvement, where they indicated that excitement on an e-bike (riding faster on an e-bike, feeling fun to ride an e-bike) was related to high perceived safety but increase in incident involvement at the same time.

The expectancy of performance of e-bikes may impact how cyclists perceive the risk relating to e-bikes. When it comes to the specific scenario of bike interactions, this thesis suggests that preconceptions about the potential dangers of e-bikes can impact perceived risk in the specific context of bike interactions. The hypothesis is formulated as follows:

- The preconception that riding an e-bike increases the involvement in crashes and causes more severe injuries would lead cyclists to perceive a higher level of risk when riding or encountering an e-bike, in comparison to riding or encountering a conventional bike.

Competence of cycling skills:

Chaurand and Delhomme (2013) studied the perceived risk of bike-car interaction and compared the perceived risk between drivers and cyclists through six hypothetical interaction scenarios by online survey. The results showed that cyclists with higher perceived competence of cycling skills would perceive less risk of bike-car interaction.

Higher competence of riding a bike was found related to less risk perception in bike-vehicle interaction. The hypothesis is formulated as follows:

- Cyclists who are more competent in cycling skills will perceive lower risk when interacting with other cyclists in traffic than cyclists who feel less competent.

Cycling behaviors:

The error and aggressive riding behaviors were found to be significant factors predicting the involvement of e-bike accidents (Yao & Wu, 2012). They used a questionnaire and constructed a structure equation model to explore the relationship between riding behaviors, risk perception, safety attitudes, and accident involvement of e-bikes. The results indicated that a high score on risk perception caused less aberrant cycling behaviors. Useche et al. (2018) developed a Cycling Behavior Questionnaire (CBQ) to investigate cycling behavior with three factors: violations, errors, and positive behaviors. Notably, with the purpose of measuring perceived risk, this research adjusted questions of error factors related to intersection. This adaptation also referenced to study by Chai et al. (2022).

The cycling behaviors and habits increased the probability of being involved in crashes and the severity of injuries. The hypothesis is formulated as follows:

- Cyclists who frequently perform erroneous and aggressive cycling behaviors tend to perceive a reduced level of risk when interacting with other cyclists in traffic, compared

to cyclists who rarely perform such aberrant cycling behaviors.

2.2.2. Bias between perceived risk and actual risk

However, the bias between perceived risk and actual crash results of cycling may lead to underestimation of actual risk (Schepers et al., 2020). It was found that though single-bicycle crashes are the majority of victims admitted to hospitals, people fear most bicycle-motor vehicle crashes. The bias between the hospitalization data and people‘s perception of bicycle crashes reflected that the danger and severity of single-bicycle crashes were underestimated, therefore the awareness of risks of single-bicycle crashes should be raised and more prevention of such crashes should be provided. Moreover, the perceived risk was found to hinder potential or occasional cyclists from accessing cycling, therefore mitigating perceived risks of cycling by better road designs could help to achieve a higher ridership and promote the prevalence of cycling (Sanders, 2015).

2.2.3. Existing methodologies for assessing perceived risk of cycling

Apart from the textual description(Chaurand & Delhomme, 2013; Haustein & Møller, 2016) commonly used in questionnaires to study the perceived risk, various alternative methodologies have been employed to investigate perception while cycling. Lehtonen et al. (2016) used video clips from cyclists' views and asked participants to continuously indicate caution in various cycling scenarios. They found that experienced cyclists would react to the hazards of cycling more frequently than inexperienced ones. A similar method was adopted by Liu et al. (2020) that the 360° videos were applied to examine the perception of satisfaction. Nazemi et al. (2021) employed the bicycle simulator to study the perceived safety of cycling and utilized virtual reality to develop various cycling environments. This design of the study method provided an immersive experience of riding and revealed the environment, traffic volume, and pedestrian factors influenced the perceived safety of riding. Besides the simulating methods, the field experiment was conducted to study the comfort and safety of riding. Fitch and Handy (2018) combined a real-world riding experiment with a video-based survey to compare the experienced and imagined comfort and safety of riding, and results indicated a systematic negative bias that less comfort and safety of riding was perceived in the video-based survey than in real riding experience.

2.3. Research gap

The existing studies that have been reviewed in this chapter have focused on safety issues of bikes and e-bikes, but the research on the interaction between them is less explored. It

is problematic because bikes and e-bikes are regulated to share the same cycling facilities, where various conflicts and crashes occur. With the emergence of e-bikes, different interactions and conflicts are introduced among e-bikes themselves and between e-bikes and bikes. As a result, bicycle safety issues have become more complex, and more demands are put forward for both traffic regulations and infrastructure designs. Therefore, a comprehensive exploration of the interaction between bikes and e-bikes enables a better understanding of bicycle safety and deserves further exploration. It is imperative to pay more attention to the risk caused by speed and behavior discrepancies of bicycle types.
Currently, there are studies on the perceived risk of conventional bikes and bike-car interaction, while there is a notable gap in the exploration of perceived risk in interactions between bikes and e-bikes. Investigating the perceived risk of bike-e-bike interactions offers a more profound understanding of bicycle safety concerns, and combining traffic environment and individual factors can provide a better comprehension of cyclists' perceptions when they are involved in critical incidents. Furthermore, conducting comparative analyses between different types of bicycles can unveil the impacts of various characteristics of bicycle types in interactions.

This thesis aims to address the above gap by looking into the impact of the type of bikes encountering (e-bike or bike), the impact of the type of bikes riding (e-bike or bike), the impact of the traffic environment (for instance the intersection type and the traffic volume), and the impact of individual factors (for instance the demographics, experience, competence, and behaviors).

2.4. Research objective and questions

The research objective is to investigate cyclists‘ perceived risk during the interaction between bikes and e-bikes, particularly to look into the impact of bicycle types ridden by participants (bike, e-bike), the bicycle types they encounter (bike, e-bike), and traffic environment and individual factors on the perceived risk in bicycle interactions. To achieve this objective, the main research question in this thesis has been defined as:

Research question: What factors affect cyclists' perceived risk in bike and e-bike interactions?

To better answer the above research question, it is divided into three sub-questions as in the following:

Sub-research question:

1. How do cyclists perceive risk when interacting with different types of bicycles? Specifically, three interactions are explored:
   (a) riding a bike, encountering a bike;
   (b) riding a bike, encountering an e-bike;
   (c) riding an e-bike, encountering a bike
2. How do traffic environment factors influence cyclists‘ perceived risk when they are interacting with other cyclists?
3. How do individual factors influence cyclists‘ perceived risk when they are interacting with other cyclists?

3

Methodology

3.1. Research design

3.1.1. Conceptual framework

In section 2.2 the factors of bike and e-bike accidents have been discussed in terms of traffic environment, cycling speed, and bicycle types. In section 2.3.1 the individual factors underlying the perceived risk of using bikes and e-bikes were explored. Summarized from the above discussions and literature review, several hypotheses have been put forward as a result of the literature review, and a tailored conceptual framework illustrated in Fig 3.1 is constructed to describe the relationship between traffic environment, bicycle type, individual factors, and the perceived risk in bike interactions.

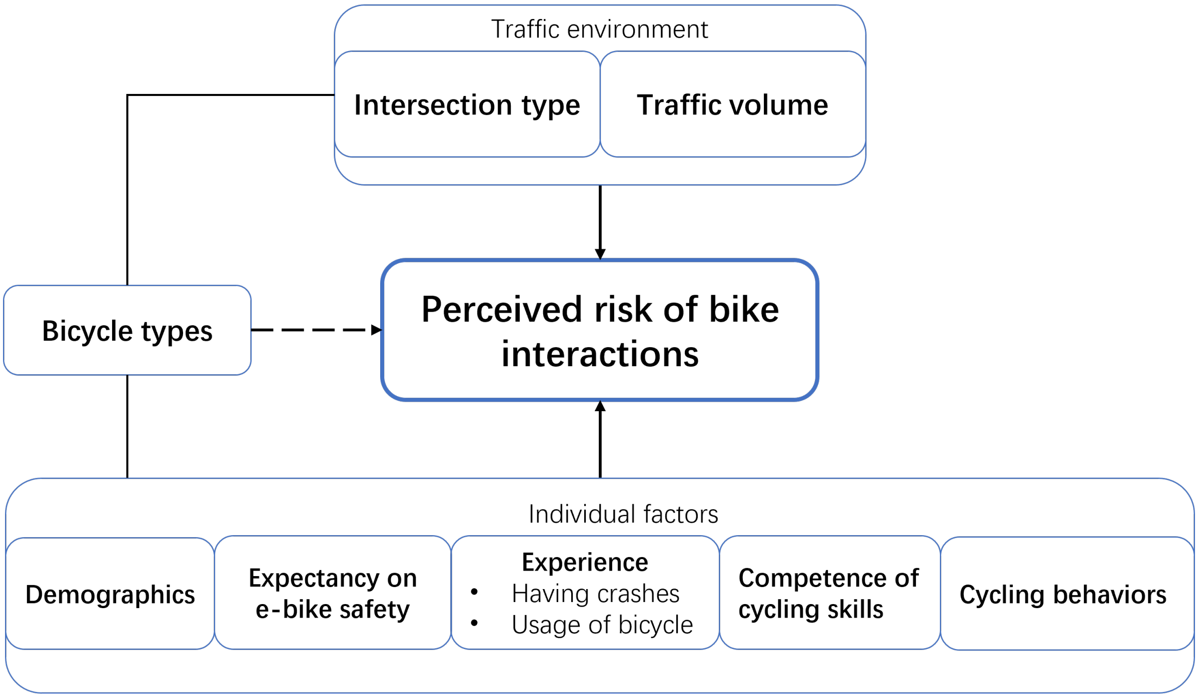

Figure 3.1: Conceptual framework of risk perception of bikes interaction

3.1.2. Research execution

In order to measure the perceived risk of cyclists, the survey method was adopted. Including several pre-recorded videos presenting traffic scenarios in the survey, allows participants to easily understand the hypothetical traffic scenarios and subsequently perceive risk in bicycle interactions. Moreover, the survey was distributed via an online platform, therefore a large sample of participants could be recruited.

To execute the research on perceived risk in bicycle interactions, four main steps were followed as shown in Fig 3.2.

Firstly, in order to present traffic scenarios close to reality and help participants better understand the hypothetical bike-e-bike interactions, several short video clips were recorded from a first-person view while cycling in the real world. The traffic environment factors and orthogonal design of traffic scenarios, the location to take the experiment of bicycle interactions, and the video recording procedures are further explained.

Next, the survey was designed to include pre-recorded videos, combined with questions to measure the perceived risk and individual factors. This online survey was developed and distributed via the Qualtrics platform.

Then, the online survey was distributed in the Netherlands. Data was collected from responses to the survey, and invalid responses were filtered.

Finally, the Stata software was used for data analysis. A random-effects ordered logit model was developed to explore the relationship between the traffic environment, bicycle types, individual factors, and the perceived risk in bicycle interactions.

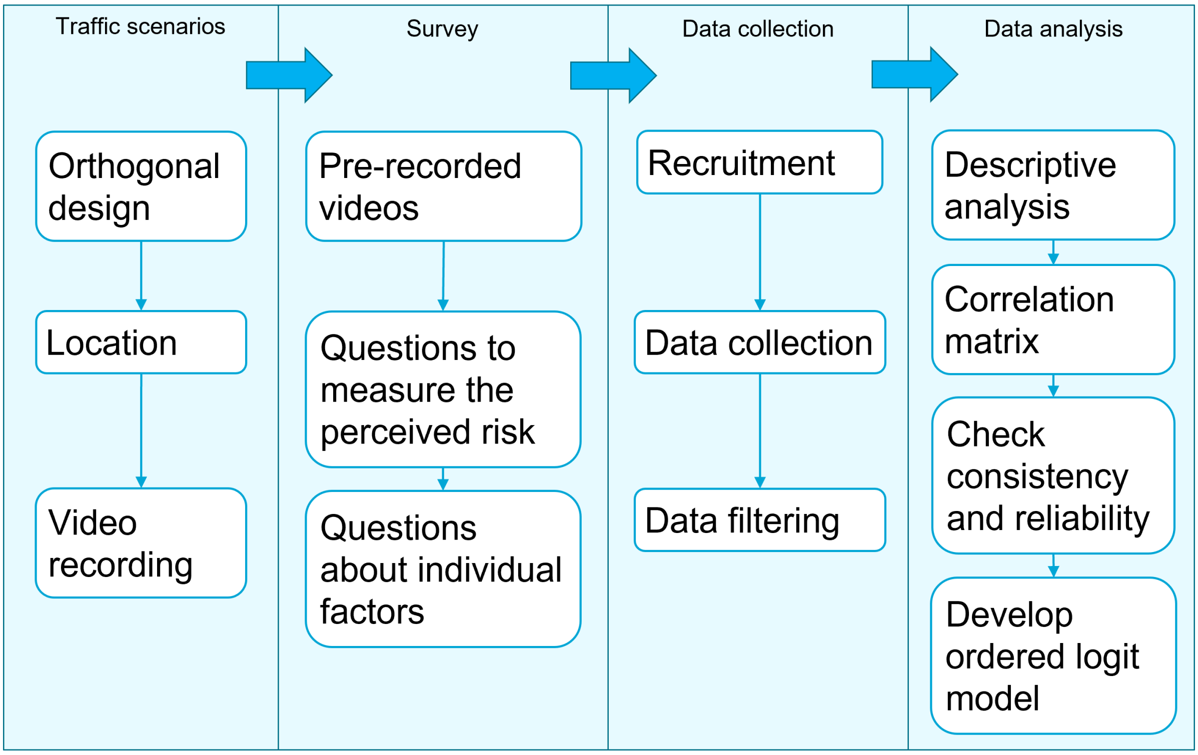

Figure 3.2: Steps of research execution

3.2. Traffic scenarios

3.2.1. Attributes and orthogonal design of traffic scenarios

Attributes:

Through literature review, it has been found that traffic environment factors and bike type had impacts on cyclists' risk perception. A bicycle interaction experiment was conducted to include these factors in traffic scenarios of bike-e-bike interactions, which were presented in the form of pre-recorded videos from the first-person view of riding a bike or an e-bike. By pre-recorded videos, the hypothetical traffic scenarios can be better understood. Later these videos showing traffic scenarios were included in the survey, based on which participants were asked to rate the perceived risk.

Derived from the literature review in section 2.2 and the conceptual framework in section 2.6, three attributes in terms of bike type, traffic volume, and intersection type were included in the bike-e-bike interaction experiment, as listed in Table 3.1.

Table 3.1: Attributes of bike interaction experiment

Attributes	levels		
Bike type	0=ride a bike, encounter an e-bike	1=ride an e-bike, encounter a bike	2=ride a bike, encounter a bike
Traffic volume	0=off-peak hour (without other cyclists)	1=peak hour (with a lot other cyclists)	
Intersection type	0= 3-leg, small size	1= 4-leg, large size	

In this research, the focus is on traffic scenarios that depict interactions between bikes and e-bikes taking place at unsignalized intersections, which is one of the most critical incidents for bikes and e-bikes (Deliali et al., 2021). Specifically, the two most frequent conflicts of bikes and e-bikes at an intersection were included in the experiment: the bike/e-bike cross straight with a bike/e-bike turning left into the opposite direction, and the bike/e-bike cross straight with bike/e-bike turning right into the same direction (Bai et al., 2013). Fig 3.3 depicts these two conflicts at an intersection.

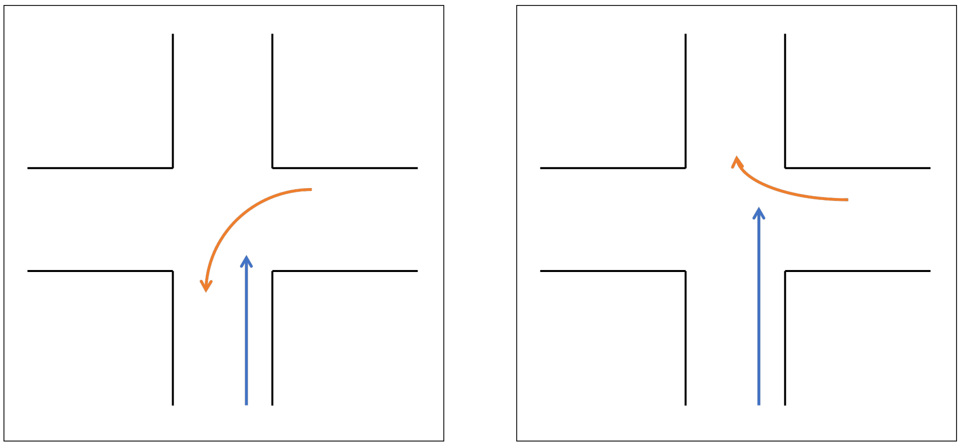

Figure 3.3: Two conflicts of bikes and e-bikes at an intersection

Orthogonal design:

In order to confirm the combination of various factors in each traffic scenario, an experiment design was conducted. In total, 1 attribute with 3 levels and 2 attributes with 2 levels composed the design and a full factorial design with 3*2*2=12 choice sets will be given. However, due to the limitation on experiment execution, as well as considering the feasibility of conducting questionnaires, a full factorial design with 12 choice sets (given two conflicts in each traffic scenario, 24 choices in total) was too large to be suitable in this case. Therefore, an orthogonal fractional factorial design was conducted, as it could effectively minimize the number of choice sets and preserve the independence between all attributes (Gunst & Mason, 2009). Furthermore, in order to decrease the number of choices in the survey, the orthogonal design was divided into two blocks, so that each participant only needed to take half of the experiment. An orthogonal design for 1 attribute with 3 levels and 2 attributes with 2 levels was designed by SPSS, and the result is shown in Table 3.2, where in total 8 choice sets were given into two survey blocks.

Table 3.2: Orthogonal design of bike interaction experiment

Survey block	Scenario No.	Bike type	Traffic volume	Intersection type
1	1	ride a bike, encounter a bike	peak	3-leg, small size
	2	ride a bike, encounter an e-bike	off-peak	3-leg, small size
	3	ride a bike, encounter an e-bike	off-peak	4-leg, large size
	4	ride an e-bike, encounter a bike	peak	4-leg, large size
2	5	ride a bike, encounter a bike	off-peak	4-leg, large size
	6	ride a bike, encounter an e-bike	peak	4-leg, large size
	7	ride a bike, encounter an e-bike	peak	3-leg, small size
	8	ride an e-bike, encounter a bike	off-peak	3-leg, small size

3.2.2. Location

Two unsignalized intersections were chosen as different locations of bike interactions. Location 1 is a 3-leg, small intersection, and location 2 is a 4-leg, large intersection. It is expected that the size of the intersection would impact cyclists' risk perception, that at small intersections cyclists would perceive higher risk compared to at large intersections because small intersec-

tions force cyclists to get close to each other and increase the probability of having collisions.
Intersection 1. As shown in Fig 3.4 and Fig 3.5, intersection1 connects way to Delft station and TU Delft campus, located in Zuideinde 232, 2627 CE Delft. It is a 4-leg intersection, with the eastern leg being a two-directional bike path on the bridge (with slope) and the other three legs are shared space for automobiles and bicycles as shown in Fig 3.6, however, the traffic flow of automobiles in this intersection is relatively low, which can be regarded that there are mere influences caused by automobiles.
The major traffic of bicycles lies on the northern and eastern legs, some on the western leg, and the southern leg has the least. Therefore, most maneuver activities are left turn from north to east and right turn from east to north.
Two conflicts of bike and e-bike at intersection1 were drawn in Fig 3.7, with the red arrow representing the encountered bike (or e-bike), and the blue arrow representing the participating bike (or e-bike). The videos were recorded from the view riding crossing the intersection (as the participating bike, indicated by a blue arrow in Fig 3.7), and encountering another bike or e-bike turning left or right (following the red arrow direction).

Figure 3.4: Street map of intersection 1

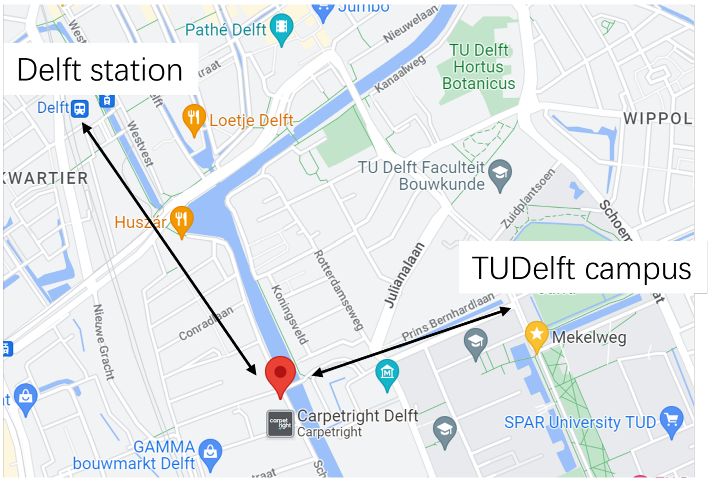

Figure 3.5: Location of intersection 1

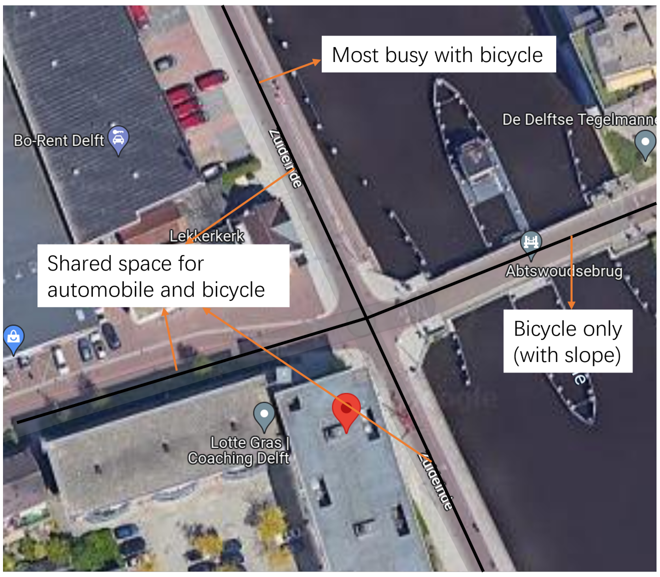

Figure 3.6: Composition of intersection 1

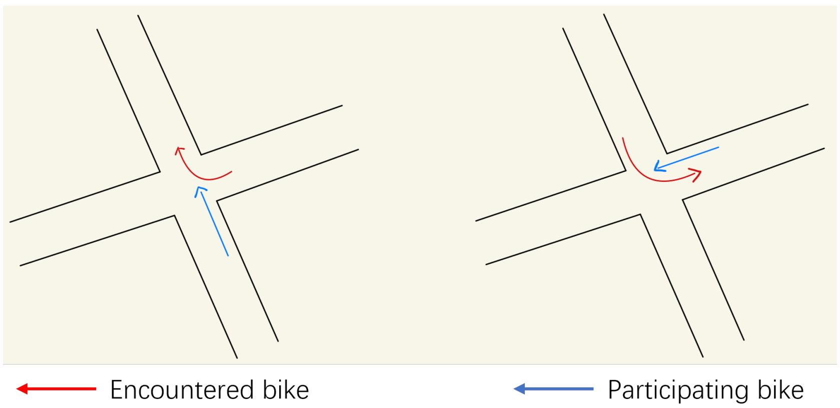

Figure 3.7: Interaction scenarios at intersection 1

Intersection 2. Shown in Fig 3.8 and Fig 3.9 intersection 2 is located on TU Delft campus (Mekelweg 3, 2628 CC Delft) as a diverge point to TU Delft Library and other faculties. It is a 3-leg intersection with all three legs are two-way bicycle paths. The only influence is the bus path next to it, with occasional cyclists having to wait at this intersection when a bus passes by. The traffic flow of bicycles is high especially when the time is close to the lecture timetable. Fig 3.10 drawn the two scenarios of bike and e-bike interactions occurring at intersection2. The color of the arrows held the same meaning as of intersection1.

Figure 3.8: Street map of intersection 2

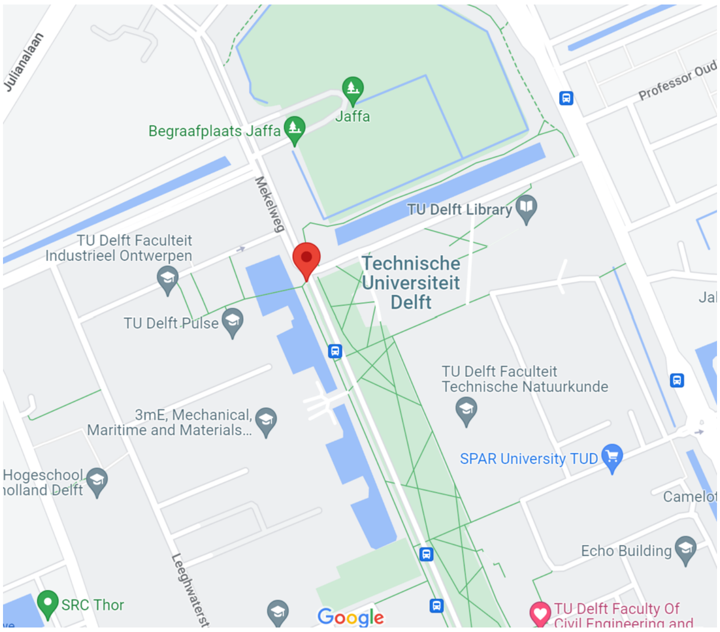

Figure 3.9: Location of intersection 2

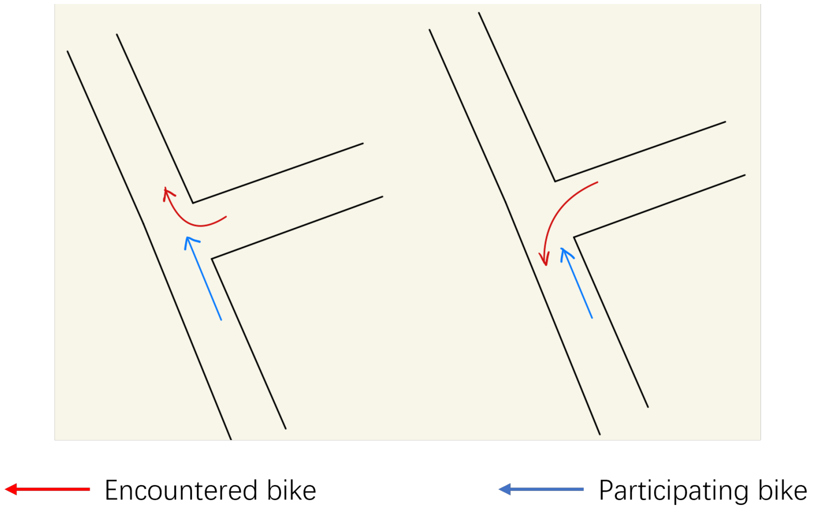

Figure 3.10: Interaction scenarios at intersection 2

3.2.3. Video recording

To increase the resemblance of the hypothetical traffic scenarios with the real-life interactions, the scenarios will be presented in the form of pre-recorded videos from the first-person view.

The video was recorded by the researcher while riding at the two intersections in Delft (mentioned above), from April to May in 2023. In order to increase the likelihood of observing the interactions between bikes and e-bikes, one volunteer who is familiar with riding a bike and an e-bike was invited to participate in video recording. He was asked to ride an e-bike and perform his normal riding maneuvers at intersections, and to encounter the researcher who was also riding and recording videos of these interactions from the first-person view.
Since the interactions were completely naturalistic and consisted of day-to-day riding maneuvers, the researcher and volunteer would not be exposed to any extra risk. In addition, a consent form was obtained from the volunteer, which explained the purpose, methodology, and all normal risks of the experiment. To protect the privacy of any people who might be present in the videos, all sensitive information (such as their faces or license plates) was blurred before showing the videos to the participants.

The recording device was the camera on iPhone 12 (with a wide-angle lens to present a wider view). In order to record the video while riding from the first-person view, the phone was attached by a neck holder mount for the motion camera, so that both hands would not be disturbed when holding the handlebars and riding the bike/e-bike.

Eventually, 16 videos presenting the traffic scenarios and showing the bike-e-bike interaction was recorded. The screenshots of each video are listed in Table 3.3.

Table 3.3: Screenshots from videos of bike-e-bike interactions

Attributes of traffic scenarios	Left turn-cross conflict	Right turn-cross conflict
Scenario 1: -Ride a bike, encounter a bike -Peak hour -At small intersection		
Scenario 2: -Ride a bike, encounter an e-bike -Off-peak hour -At small intersection		
Scenario 3: -Ride a bike, encounter an e-bike -Off-peak hour -At large intersection		
Scenario 4: -Ride an e-bike, encounter a bike -Peak hour -At large intersection		

Scenario 5: -Ride a bike, encounter a bike -Off-peak hour -At large intersection		
Scenario 6: -Ride a bike, encounter an e-bike -Peak hour -At large intersection		
Scenario 7: -Ride a bike, encounter an e-bike -Peak hour -At small intersection		
Scenario 8: -Ride an e-bike, encounter a bike -Off-peak hour -At small intersection		

3.3. Survey design

The perceived risk of bike interactions was investigated through an online survey. In this survey, data was collected by a questionnaire. Derived from the conceptual framework in section 3.1, several questions were put forward in regard to traffic environment, bicycle type, individual factors, and perceived risk of cycling.

3.3.1. Questionnaire

The traffic environment factors and bicycle type were presented in the form of video recordings showing specific traffic scenarios, and perceived risk was measured by two questions: a) rate of perceived risk, and b) likelihood of being involved in crashes. In total 8 videos showing bike and e-bike interaction were presented in the questionnaire, with each having two questions to measure perceived risk. Therefore totally there were 16 questions on perceived risk measurement. Each participant watched 8 video recordings (either of scenarios 1-4 or of scenarios 5-8, as explained in section 3.2.1, the whole experiment was divided into two survey blocks). Each video lasted around 10 seconds and showed the bike and e-bike interacting at an intersection. Every time after watching one video, participants were asked to rate their perceived risk and the likelihood of being involved in a crash on a 5-point scale (Chaurand & Delhomme, 2013; Lehtonen et al., 2016).

In addition, their individual characteristics in terms of demographics, cycling experience, competence of riding skills, cycling behaviors, and expectancy on e-bikes were asked in the survey. These individual factors were measured by the other 17 questions. The detailed question descriptions and references are listed in Table 3.4. In all, 33 questions were included in the questionnaire.

Table 3.4: Research variables and questionnaire items

Variable	Item	Description	Question reference
Perceived risk measurement (repeat 8 times)	a) How do you rate your perceived risk when riding in this scenario?	Rate the perceived risk with 1 to 5 scales. 1=Not risky at all, 5= very risky	Fitch & Handy, 2018; Parkin et al., 2007; Sanders, 2015
	b) How likely is it that you will be involved in a crash if you ride in this scenario?	Indicate the likelihood with 1 to 5 scales. 1=very unlikely, 5=very likely	Lehtonen et al., 2016,
Demographics	1. What is your age? 2. What is your gender? 3. What is the highest level of education that you have completed?		Cycling Behavior Questionnaire (Useche et al., 2018)
Usage of bicycle	4. What type of bicycle do you typically ride? 5. What is your primary motivation for riding a bike/an e-bike? 6. How many hours do you spend riding a bike/an e-bike on an average week?		Cycling Behavior Questionnaire (Useche et al., 2018)

Experience of crashes	7. How many crashes have you experienced while riding a bike/an e-bike on the road in the past 3 years (Crash here refers to any incident involving a vehicle, bike or pedestrian that resulted in a personal injury, damage to a vehicle or other property)?		Cycling Behavior Questionnaire (Useche et al., 2018)
Cycling behaviors	8. I feel that the actual speed of riding is faster than I should keep. 9. I compete with other bicycles and e-bikes at intersections. 10. I keep a close distance from other cyclists across the intersection.	Indicate frequency to perform behaviors with 1 to 5 scales. 1=never, 5=always	Cycling Behavior Questionnaire (Useche et al.,2018), Chai et al., 2022
Competence of cycling skills	11. I can control my cycling no matter how fast I‘m going. 12. I can control my cycling no matter how heavy the traffic is. 13. I‘m typically confident when cycling at an intersection.	Indicate agreement with 1 to 5 scales. 1= strongly disagree, 5 = strongly agree	Chaurand & Delhomme, 2013
Expectancy on e-bike safety	14. In general, it is riskier to ride an e-bike than a conventional bike. 15. I prefer an e-bike to a conventional bike for daily cycling.	Indicate agreement with 1 to 5 scales. 1= strongly disagree, 5 = strongly agree	Haustein and Møller (2016)

	16. In case of an accident, there is a higher chance of getting injured with an e-bike than a conventional bike. 17. In case of an accident, there is a chance to get more severely injured with an e-bike than a conventional bike.

3.3.2. List of candidate explanatory variables

Derived from the above questions, a more detailed list of candidate explanatory variables is shown in Table 3.5.

Table 3.5: List of candidate explanatory variables

Category	Variable	Description
Dependent variable	Rate of perceived risk	scale from 1 to 5, 1= not risky at all, 5=very risky
	Likelihood of being involved in a crash	scale from 1 to 5, 1= very unlikely, 5=very likely
Independent variable (within-in participants)	Bike type	0=ride a bike, encountering an e-bike 1=ride an e-bike, encountering a bike 2=ride a bike, encountering a bike
	Traffic volume	0=off-peak (no other cyclists) 1=peak (with a lot other cyclists)
	Intersection type	0=3-leg, small size 1=4-leg, large size
	Conflict	0=left turn-crossing conflict 1=right turn-crossing conflict

Independent variable (between participants)	Age	continuous variable
	Gender	1=male
		2=female
		3=not indicate
	Education	1=high school diploma or lower
		2=Trade/technical/vocational training
		3=bachelor's degree
		4=Master's degree
		5=PhD
		6=not indicate
	Type of cyclist	1=bike user
		2=e-bike user
	Motivation for cycling	1=work or business
		2=education
		3=shopping
		4=leisure or recreation
		5=fitness or exercise
		6=not indicate
	Weekly cycling hours	continuous variable
	Number of crashes	continuous variable
	Expectancy on e-bike safety	4 items, scale from 1 to 5, 1=strongly disagree, 5=strongly agree
	Cycling behaviors	3 items, scale from 1 to 5, 1=never, 5= always
	Competence of cycling skills	3 items, scale from 1 to 5, 1=strongly disagree, 5=strongly agree

3.4. Data collection

The survey recruitment was approved by the Human Ethics Research Application of TU Delft in April 2023 (reference no.2979). At the start of the survey, an opening statement was given to collect participants‘ data.

The recruitment was conducted in two ways. The first was by snowballing. The researcher distributed the questionnaire by email to her networks (friends, schoolmates, and lecturers), and encouraged the participants to share the questionnaire with their networks. The second was by advertising. The posters with the survey description and QR code were put up in several faculties and the library of TU Delft. As a result, the survey was mostly distributed among university students.

The recruitment was conducted in July 2023, and in total 134 participants responded and finished the survey. One invalid response with no individual information and 5 responses from non-bicycle users were excluded. Because non-bicycle users never or seldom have experienced using a bike or an e-bike, they may hardly imagine the hypothetical traffic scenarios of bike interactions and perceive any risk of cycling, which would cause bias in the measurement of perceived risk. As a result, the 5 responses from non-bicycle users were excluded eventually.

Totally 128 valid responses from conventional bike users and e-bike users were analyzed.

3.5. Data analysis

At the start, a descriptive analysis is conducted on all variables to gain an overall review of the results. Moreover, the individual factors are compared between bike users and e-bike users, and statistical tests of the t-test and Mann-Whitney U test are employed to assess these differences.

In this research, perceived risk is measured by the rate and the likelihood of being involved in a crash with a 5-point scale. The dependent variable is ordinal and discrete, therefore the ordered logit model is used to explore the relationship between perceived risk and traffic environment and individual factors (Liu et al., 2020). And considering the panel effects that each participant has 8 observations of data, the random-effects ordered logit model is explored (Conaway, 1990).

To express random-effects ordered logit model in terms of a latent linear response, the ordinal responses y_{it}, perceived risk of bike interactions, are generated from the latent continuous responses, such that:

$$y^*_{it} = x_{it}\beta + \upsilon_i + \epsilon_{it} \tag{3.1}$$

and

$$y_{it} = \begin{cases} 1 & \text{if } y^*_{it} < \kappa_1 \\ 2 & \text{if } \kappa_1 < y^*_{it} < \kappa_2 \\ ... & \\ 5 & \text{if } \kappa_4 < y^*_{it} \end{cases} \tag{3.2}$$

for $i = 1, ..., n$ panels, where $t = 1, ..., n_i$,
x_{it} represents the independent variables,
β represents the coefficients of independent variables,
υ_i are independent panel-level random effects,
the errors ϵ_{it} are distributed as logistic and are independent of υ_i,
and κ is a set of cut-off points.

The dependent variables of rate and likelihood of being involved in a crash scale from 1 to 5, therefore, the model structure of the ordered logit model is shown as:

$$\ln\left(\frac{P(y_{it}=1)}{1-P(y_{it}=1)}\right) = x_{it}\beta + v_i$$

$$\ln\left(\frac{P(y_{it}=1)+P(y_{it}=2)}{1-P(y_{it}=1)-P(y_{it}=2)}\right) = x_{it}\beta + v_i$$

$$\ln\left(\frac{P(y_{it}=1)+P(y_{it}=2)+P(y_{it}=3)}{1-P(y_{it}=1)-P(y_{it}=2)-P(y_{it}=3)}\right) = x_{it}\beta + v_i \tag{3.3}$$

$$\ln\left(\frac{P(y_{it}=1)+P(y_{it}=2)+P(y_{it}=3)+P(y_{it}=4)}{1-P(y_{it}=1)-P(y_{it}=2)-P(y_{it}=3)-P(y_{it}=4)}\right) = x_{it}\beta + v_i$$

Where P represents the probability of perceived risk level:

$$P(y_{it}=1|\kappa, x_{it}, v_i) = \frac{1}{1+exp(-\kappa_1 + x_{it}\beta + v_i)}$$

$$P(y_{it}=j|\kappa, x_{it}, v_i) = \frac{1}{1+exp(-\kappa_j + x_{it}\beta + v_i)} - \frac{1}{1+exp(-\kappa_{j-1} + x_{it}\beta + v_i)} \tag{3.4}$$

$$P(y_{it}=5|\kappa, x_{it}, v_i) = 1 - \frac{1}{1+exp(-\kappa_4 + x_{it}\beta + v_i)}$$

The random-effect ordered logit model is estimated using the maximum likelihood procedure. Through inputting dependent variables (rate and likelihood of perceived risk) separately and independent variables (traffic environmental factors, bicycle types, and individual factors), the outcomes of the model are estimated coefficients of each independent variable (β value) and four cut-off points (κ value). These coefficients allow us to interpret the impact of each independent variable on perceived risk.

4

Results

The results section is developed in three sub-sections, where the first section conducts the descriptive analysis of all explanatory variables, and the second section develops and estimates the ordered logit model. Finally, the third section discusses the results from the ordered logit model.

4.1. Descriptive analysis

4.1.1. Respondents` characteristics

Table 4.1 and pie charts in Fig 4.1 show the descriptive statistics of respondents' characteristics. The sample is relatively youthful, with an average age of 27 years (standard deviation = 7.36, range from 18 to 74). Out of the 128 respondents, the majority belong to the younger group aged between 18 and 29 years old (comprising 81.3% of respondents). In contrast, the middle-aged group (30-50) and the older age group (over 50) constitute a small part of the sample (only 13.3% and 3.1% respectively of the total). The gender distribution of the sample is nearly even, with 62 males and 62 females. Regarding educational background, respondents exhibit diversity, yet a significant proportion, nearly 80%, hold either a Bachelor's or Master's degree.

In terms of cycling characteristics, there is a notable imbalance among respondents. A significant majority are conventional bike users (83.6%), whereas only a few use e-bikes (16.4%). For those who ride both a bike and an e-bike, they are regarded as e-bike users. When examining the motivations for cycling, nearly 80% of respondents use bicycles or e-bikes for commuting purposes. Specifically, 30.5% ride for work or business, and 45.3% for education. Only a small fraction cite shopping, leisure, or fitness as their primary motivations (10%, 10%, and 3% respectively).

On average, participants in the study spend 3.59 hours cycling per week (standard deviation = 2.48). This weekly riding time varies, with a minimum of 0.3 hours and a maximum of 11.5 hours. Interestingly, e-bike users tend to spend more time cycling, averaging 4.97 hours per week, which is statistically significantly (p=0.05) higher than traditional bike users, who average 3.32 hours per week. This variance in average weekly riding hours between the two types of bikes may be attributed to the differing demands and ease of cycling. Individuals with higher cycling demands may find e-bikes more suitable for daily use due to their ease of use and lower physical exertion compared to traditional bikes.

Regarding bicycle crashes resulting in personal injury, or damage to a vehicle or other property, over half of the respondents reported no crashes in the past 3 years. Of the remaining respondents, 21.9% experienced one crash, while 12.5% reported two crashes and another 12.5% experienced more than two crashes. On average, participants experienced 0.98 crashes (standard deviation = 1.45), with a maximum of 8 crashes. Bike users, on average, experienced slightly more crashes, averaging 1.03, compared to e-bike users, who averaged 0.76 crashes. However, the variation in crash numbers between the group of bike users and the group of e-bike users is insignificant according to the t-test result (p=0.47).

Table 4.1: Descriptive statistics of continuous variables

Variable	mean	std.	min	max
Age	27.04	7.36	18	74
Weekly riding hours (total)	3.59	2.48	0.3	11.5
Weekly riding hours (Bike rider)	3.32	2.16	0.3	10
Weekly riding hours (E-bike rider)	4.97	3.48	0.5	11.5
Number of crashes (total)	0.98	1.45	0	8
Number of crashes (Bike rider)	1.03	1.48	0	8
Number of crashes (E-bike rider)	0.76	1.37	0	5

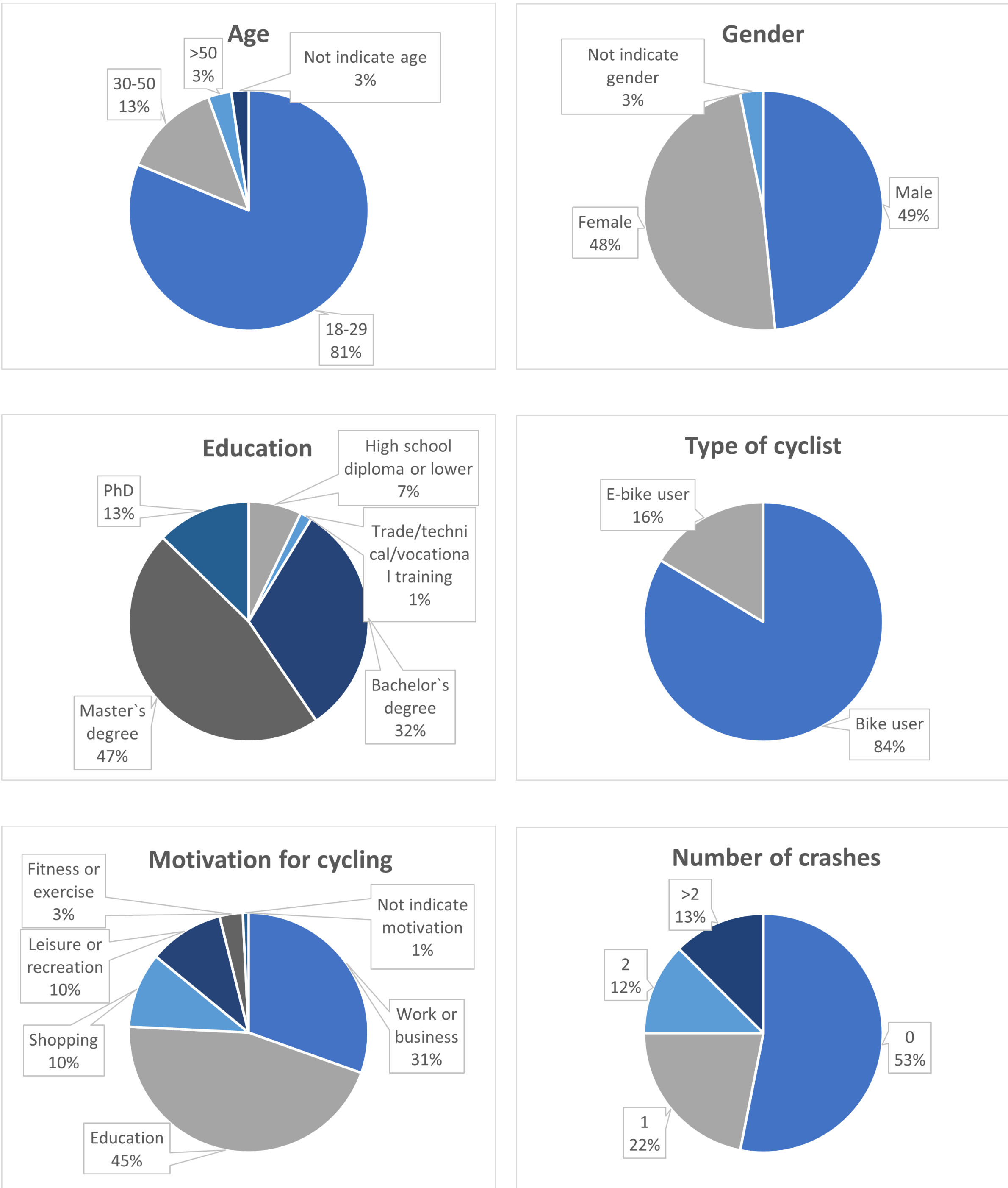

Figure 4.1: Descriptive statistics of respondent characteristics

4.1.2. Distribution of expectancy, competence and behaviors

The agreements on questions about the expectancy on e-bike safety, competence of cycling skills and cycling behaviors are separately illustrated in terms of different groups of cyclists. As compared in Fig 4.3 - Fig 4.7, the distribution of agreements is similar between the group of bike users and the group of e-bike users, except for the question about the preference to use an e-bike for daily cycling. Moreover, as Table 4.2 shows, the mean scores and standard deviation are calculated, and the Mann-Whitney U test is conducted to examine the difference between different groups of cyclists, where only the agreement of the preference to use an e-bike is found statistically significantly different (p=0.08) between bike users and e-bike users.

Table 4.2: Mean and standard deviation (SD) of expectancy, behavior and competence

Variable	Type of cyclists	
	Bike user [mean(SD)]	E-bike user [mean(SD)]
Expectancy on e-bike safety (1=strongly disagree, 5=strongly agree)		
In general, it is riskier to ride an e-bike than a conventional bike.	3.14(1.23)	3.19(1.03)
I prefer an e-bike to a conventional bike for daily cycling.	3.21(1.34)	3.76(1.18)
In case of an accident, there is a higher chance of getting into an accident with an e-bike than with a conventional bike.	3.27(1.20)	3.10(.89)
In case of an accident, there is a chance of getting more severely injured with an e-bike than with a conventional bike.	3.56(1.20)	3.33(1.06)
Competence of cycling skills (1=strongly disagree, 5=strongly agree)		
I can control my riding no matter how fast I‘m going.	2.96(1.25)	2.86(1.01)
I can control my riding no matter how heavy the traffic is.	3.40(1.28)	3.48(1.21)
I‘m typically confident when riding at an intersection.	3.34(1.23)	3.43(1.29)

Cycling behaviors (1=never, 5=always)		
I feel that the actual speed of riding is faster than I should keep.	2.09(1.09)	2.00(.95)
I compete with other bicycles and e-bikes at intersections.	1.74(.96)	1.71(.72)
I keep a close distance from other cyclists across the intersection.	2.52(1.13)	2.76(1.14)

Expectancy on e-bike safety:

The results concerning expectations regarding e-bike safety issues are presented in Fig 4.2 and Fig 4.3. According to these results, almost half of the respondents agree with the opinion that e-bike is in general more risky than conventional bike.

For preferences related to using e-bikes for daily cycling, the opinions are scattered among bike users, while more than half of the e-bike users express a preference for e-bikes over conventional bicycles.

The third question is about the chance of having e-bike accidents, the majority of the bike users agree with the idea, while most e-bike users hold the neutral opinion that e-bikes are more likely to get into an accident.

The fourth question is about the severity of e-bike accidents, the most of the respondents agree that there is a chance of getting more severely injured with an e-bike than with a conventional bike.

The bar charts in Fig 4.2 and Fig 4.3 reveal that, for all four questions, the majority of respondents fall into the ”somewhat agree” category. This outcome suggests that respondents generally perceive a higher overall risk associated with e-bikes.

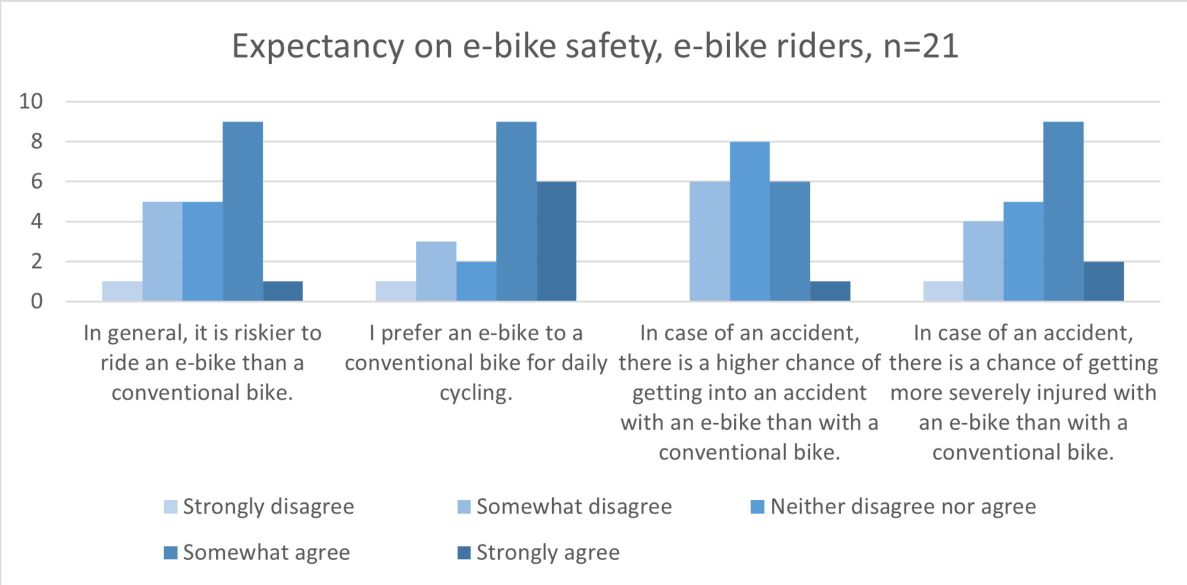

Figure 4.2: Distribution of expectancy on e-bike safety (e-bike users)

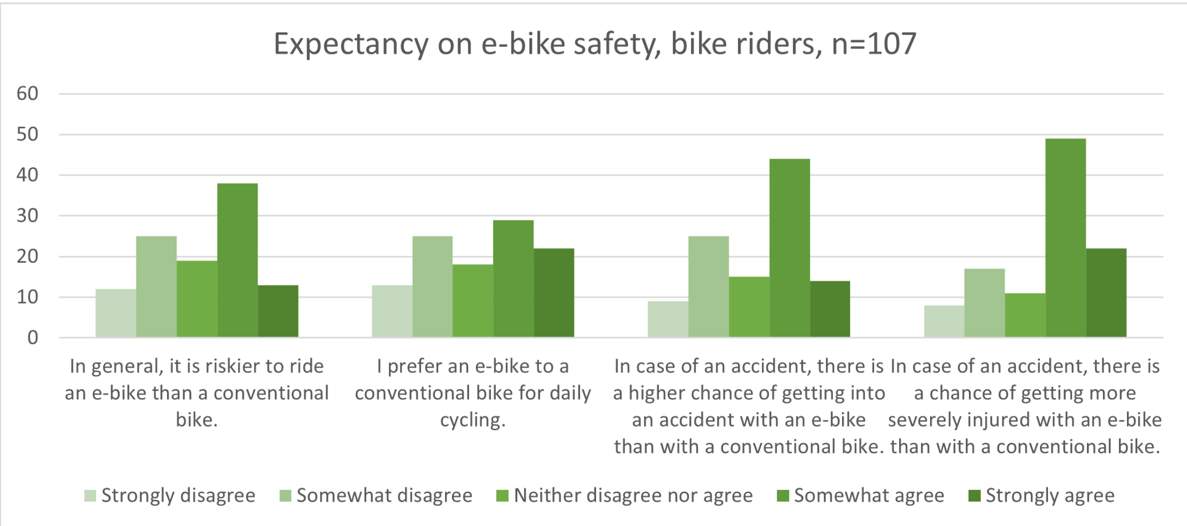

Figure 4.3: Distribution of expectancy on e-bike safety

Competence of cycling skills:

The agreements of competence of cycling skills are present in Fig 4.4 and Fig 4.5, and the distribution is similar for bike users and e-bike users. The three questions focus on the different aspects of the factors that may affect the competence of cycling: the cycling speed, the surrounding traffic, and cycling at an intersection. The overall trends are similar for the three questions where respondents either somewhat disagree or somewhat agree that they have competence of cycling skills. More respondents disagree that they have control when riding fast, while more respondents agree that they have control in heavy traffic and feel confident riding at an intersection.

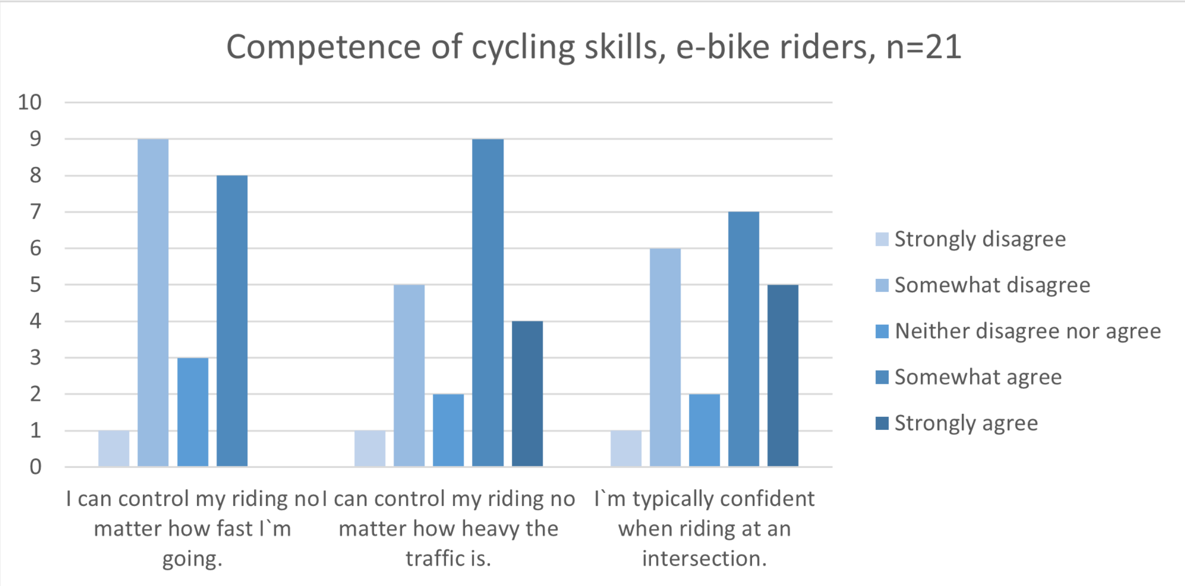

Figure 4.4: Distribution of competence of cycling skills (e-bike users)

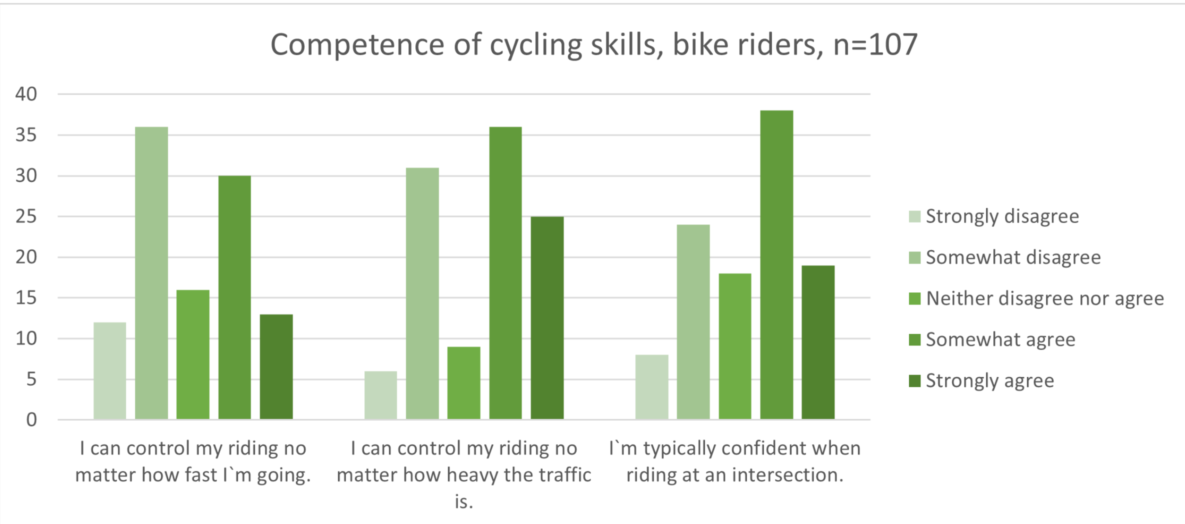

Figure 4.5: Distribution of competence of cycling skills (bike users)

Cycling behaviors:

The agreements of cycling behaviors are illustrated in Fig 4.6 and Fig 4.7. Across all three questions, the categories of 'never' and 'sometimes' encapsulate the majority of responses. For the question concerning the speed of cycling, most respondents never or sometimes exceed the appropriate speed. As for competing with other bicycles and e-bikes, more than 80 percent of respondents never or only sometimes compete with others. About half respondents sometimes keep a close distance from other cyclists at the intersection. Overall, most of the respondents are less likely to engage in risky cycling behaviors.

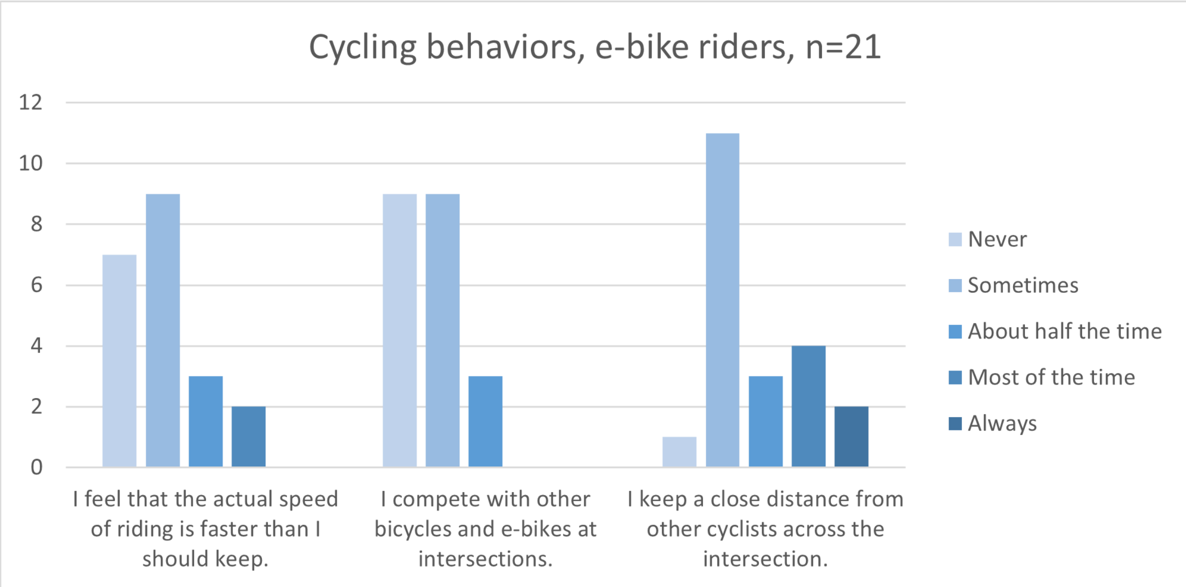

Figure 4.6: Distribution of cycling behaviors (e-bike users)

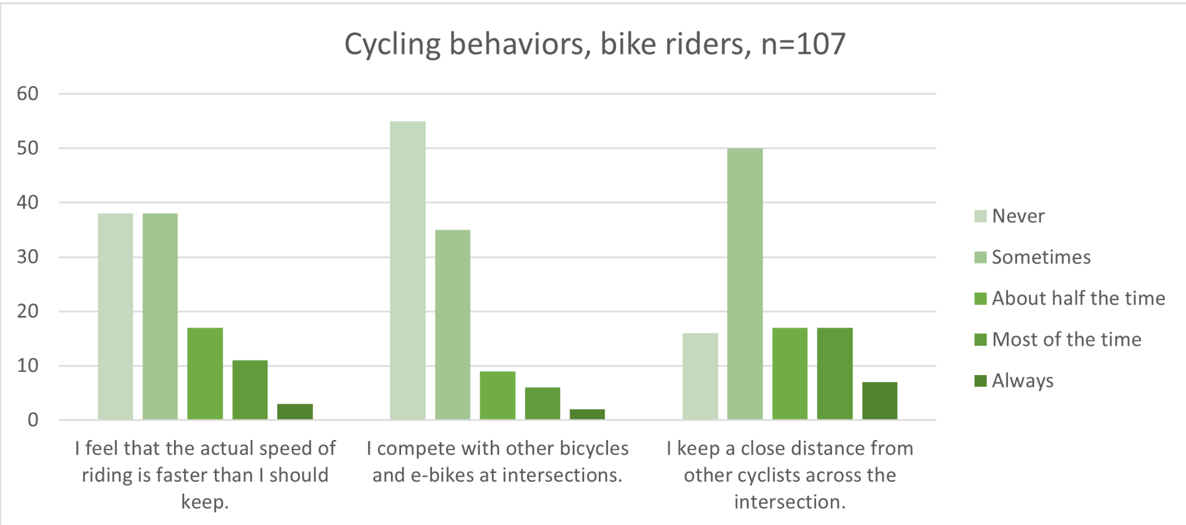

Figure 4.7: Distribution of cycling behaviors (bike users)

4.1.3. Distribution of perceived risk

Rate of perceived risk

The results regarding the question about the rate of perceived risk are shown in Table 4.3. The frequency of the not risky at all only takes 15.82% while the risky level 5 only takes 7.23% of total samples. The present time of risk level 2, level 3, and level 4 are more even distributed.

Likelihood of being involved in a crash

The results of the likelihood of being involved in a crash are shown in Table 4.3. The category ”very likely” comprises the smallest percentage at 4.88%. Most respondents either believe it is somewhat unlikely to be involved in a crash or believe it is somewhat likely to be involved in a crash.

Table 4.3: Distribution of perceived risk

Rate of perceived risk	Frequency	Percentage
1 = not risky at all	162	15.82%
2	280	27.34%
3	293	28.61%
4	215	21%
5 = very risky	74	7.23%
Total	1,024	100%
Likelihood of being involved in a crash	Frequency	Percentage
1 = very unlikely	208	20.31%
2	330	32.23%
3	176	17.19%
4	260	25.39%
5 = very likely	50	4.88%
Total	1,024	100

4.2. Ordered logit model

The relationship between perceived risk and various explanatory variables is explored using the ordered logit model. Firstly the correlation between each pair of variables is tested, and the consistency of items inside expectancy, cycling behaviors, and competence of cycling skills is evaluated by Cronbach‘s alpha. Then the process to construct an ordered logit model is described. Finally shows the final results of the model and the interpretation.

4.2.1. Correlation matrix

Firstly the correlation among all explanatory variables is checked by a correlation matrix, the details can be found in Appendix A. The correlation matrix produced scores of Pearson‘s correlation, which can vary from -1 to +1. Two objects with a high score (near +1) are highly similar, and two objects correlated inversely would have a Pearson score near -1. While two uncorrelated objects would have a score near 0 (Berman, 2016).

In this research, it’s worth noting that all the explanatory variables, with the exception of ’Expectancy on e-bike safety,’ ’Cycling behaviors,’ and ’Competence of cycling skills,’ exhibit correlation scores of less than 0.3 with each other. This suggests that the correlations of these variables are quite small, allowing us to incorporate them into the ordered logit model simultaneously.

On the other hand, within the categories of ’Expectancy on e-bike safety’ (with 4 items), ’Cycling behaviors’ (with 3 items), and ’Competence of cycling skills’ (with 3 items), there are notable high correlation scores among the individual items (correlation coefficients significant at 5% level, as shown in Appendix A). This is unsurprising, as these items are designed to measure related aspects of expectancy, behaviors, or competence and are inherently interconnected. Therefore, when constructing the ordered logit model, it is prudent to include only one representative item from each of these variables to avoid redundancy.

Alternatively, it can alternatively use the average scores to represent the entirety of each variable, which will be further discussed in the following subsection.

4.2.2. Consistency of expectancy, behaviors and competence

As variables in terms of expectancy on e-bike safety, cycling behaviors, and competence of cycling skills are measured by multiple items, the consistency of each variable is evaluated by the coefficient of Cronbach‘s alpha. Cronbach‘s alpha is used to measure the homogeneity of the items inside each variable and to evaluate the reliability and internal consistency. Following the research by Yao and Wu (2012), the values of alpha equal to or exceeding 0.7

indicated acceptable reliability.

The descriptive statistics and Cronbach‘s alpha for expectancy on e-bike, cycling behaviors, and competence of cycling skills are listed in Table 4.4. Results have shown that the variable ’Competence of cycling skills’ has the value of Cronbach‘s alpha greater than 0.7, indicating that the reliability is acceptable. The scores of three items inside the ’Competence’ variable can be averaged into one index and represent this variable in forming the subsequent ordered logit model. Higher scores reflected a stronger presence of competence of cycling skills.
On the other hand, the coefficients of variables ’Expectancy on e-bike safety’ and ’Cycling behaviors’ are less than 0.7, indicating the internal inconsistency of the two variables. For the expectancy on e-bike safety, one item goes for the preference to use an e-bike for daily cycling, while the other three items are about safety issues. The reason for inconsistency could be that when considering the preference to use an e-bike, safety issues only take a small part of the influence. For cycling behaviors, three items relate to different risky cycling behaviors. The mean score for the item ’compete with other cyclists’ is relatively lower than the other two items ’ride faster than I should keep’ and ’keep a close distance from other cyclists’. The possible reason can be these cycling behaviors exhibit different levels of risk, that competing cycling with other cyclists at intersections might be more dangerous than riding fast or keeping close distance with other cyclists.
Because of the inconsistency of variables, the reliability of ’Expectancy on e-bike safety’ and ’Cycling behaviors’ are regarded as unacceptable. When generating the ordered logit model, each time only one item of each variable would be included in the model.

Table 4.4: Descriptive statistics for expectancy, behaviors and competence

Variable	Mean	Std. dev.	Cronbach's alpha
Expectancy on e-bike safety (1=strongly disagree, 5=strongly agree)			0.683
In general, it is riskier to ride an e-bike than a conventional bike.	3.15	1.20	
I prefer an e-bike to a conventional bike for daily cycling.	3.30	1.32	
In case of an accident, there is a higher chance of getting into an accident with an e-bike than with a conventional bike.	3.24	1.16	
In case of an accident, there is a chance of getting more severely injured with an e-bike than with a conventional bike.	3.52	1.18	
Cycling behaviors (1=never, 5=always)			0.483
I feel that the actual speed of riding is faster than I should keep.	2.08	1.06	
I compete with other bicycles and e-bikes at intersections.	1.73	0.93	
I keep a close distance from other cyclists across the intersection.	2.56	1.13	
Competence of cycling skills (1=strongly disagree, 5=strongly agree)			0.753
I can control my riding no matter how fast I'm going.	2.95	1.21	
I can control my riding no matter how heavy the traffic is.	3.41	1.26	
I'm typically confident when riding at an intersection.	3.35	1.23	

4.2.3. Constructing random-effects ordered logit model

The perceived risk of interaction between bikes and e-bikes was measured by two ordinal dependent variables: the rate of perceived risk and the likelihood of being involved in a crash (both have scores from 1 to 5). Two separate random-effects ordered logit models were constructed exploring the relationship between each dependent variable and explanatory variables.

At first, traffic environment factors in terms of 'bicycle type', 'traffic volume', 'intersection type', and 'conflict' were tested in the ordered logit model. The coefficients of all these four variables were significant at 5% level in both models of 'rate of perceived risk' and 'likelihood of being involved in a crash'. Therefore all these four variables were included in the model.
Next the demographic variables in terms of 'age', 'gender', and 'education' were put into the model, systematically testing each one individually. However, only the 'age' variable exhibited statistical significance and was included in the model of 'likelihood of being involved in a crash'.
The variables of cycling characteristics were tested. 'Type of cyclist' 'motivation for cycling' 'weekly cycling hours' and 'number of crashes' were put into the model and tested individually. Results showed that the 'number of crashes' was statistically significant in both models. While 'type of cyclist' 'motivation for cycling' and 'weekly riding hours' were insignificant and thus excluded from the model.
Finally, 4 items of 'expectancy on e-bike safety', 3 items of 'cycling behaviors', and 3 items of 'competence of cycling skills' were tested individually, and the average score of 'competence of cycling skills' was also tested in the model. Results indicated that the item 'prefer to use an e-bike for daily cycling' was significant in both models and all 3 items of 'competence of cycling skills' and the average score of 'competence of cycling skills' were significant in both models. Therefore the average score was included in the model to get a better fit. While all 3 items of 'cycling behaviors' were insignificant.

After testing all independent variables, variables with significant coefficients were included in the model, while insignificant variables were excluded. By identifying significant variables, the test of the parallel line was conducted for the ordered logit model of each dependent variable, and results showed that both models satisfied the parallel line assumption, proving the relationship between the independent variable and dependent variables can be explored through the ordered logit model (Williams, 2016).

4.2.4. Final results

The random-effects ordered logit model of the rate of perceived risk and likelihood of being involved in a crash has been confirmed by the above steps. The results are shown in Table 4.5. Fig 4.8 and Fig 4.9 illustrate the visual representation of model results.

In the random-effects ordered logit model of the rate of perceived risk, 'bicycle type in the interaction' (only level 2 of riding an e-bike, encountering a bike is significant, while level 1 of riding a bike, encountering an e-bike is insignificant), 'traffic volume' 'intersection type' 'conflict' 'number of crashes' 'prefer to use an e-bike for daily cycling' and 'competence of cycling skills' are significant.

For the dependent variable 'likelihood of being involved in a crash', in the random-effects ordered logit model, the above-mentioned variables are also significant, additionally, the 'age' variable is significant.

Moreover, the significance of the estimated panel-level variance component labeled sigma2-u in both models indicates that there is enough variability to favor a random-effects ordered logistic regression over a standard ordered logistic regression (Conaway, 1990).

Table 4.5: Results of Random-effects ordered logit model

Variable	Rate of perceived risk			Likelihood of being involved in a crash		
	Coeff.	Std.err.	Odds	Coeff.	Std.err.	Odds
Bicycle type in the interaction						
0=riding a bike, encountering a bike	0a			0a		
1=riding a bike, encountering an e-bike	-0.179	0.145	0.836	0.023	0.151	1.023
2=riding an e-bike, encountering a bike	-0.932***	0.172	0.394	-0.763***	0.181	0.466
Traffic volume						
0=off-peak hour (no other road users)	0a			0a		
1=peak hour(with a lot other road users)	0.300**	0.119	1.349	0.246**	0.124	1.279
Intersection type						
0=3-leg, small size	0a			0a		
1=4-leg, large size	-0.762***	0.121	0.467	-0.713***	0.126	0.49
Conflict						
0=left turning-crossing conflict	0a			0a		
1=right turning-crossing conflict	-1.037***	0.123	0.354	-0.740***	0.126	0.477
Number of crashes	0.219**	0.107	1.245	0.297**	0.117	1.346
Prefer to use an e-bike for daily cycling	0.317**	0.118	1.373	0.345**	0.127	1.412
Competence on riding skills	-0.586***	0.156	0.556	-0.805***	0.171	0.447
Age				-0.060**	0.023	0.942
Sigma2_u	2.776***	0.454		3.260***	0.546	
Log-likelihood	-1321.678			-1220.682		

a.Reference category for the associated categorical variable.

*p<.1; **p<.05; ***p<.01

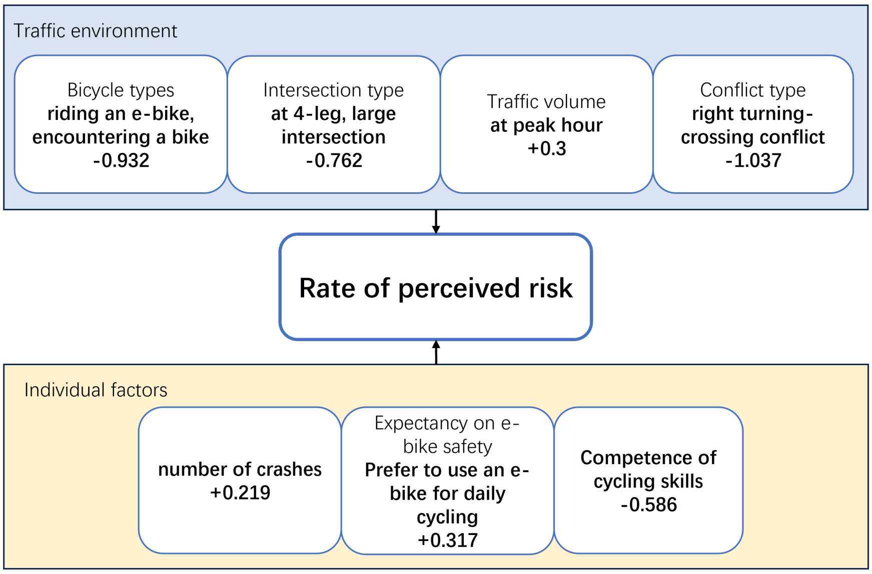

Figure 4.8: Effects of significant variables on rate of perceived risk (random-effects ordered logit model)

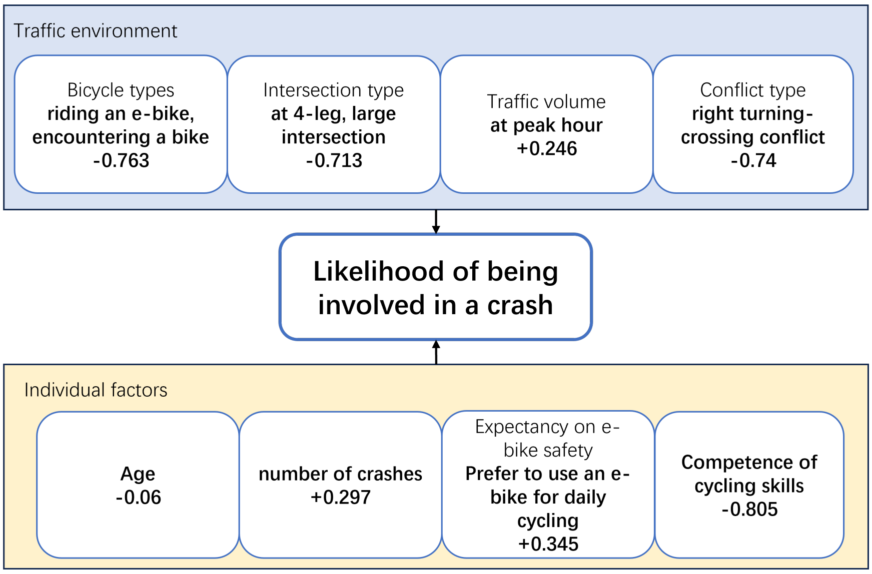

Figure 4.9: Effects of significant variables on likelihood of being involved in a crash (random-effects ordered logit model)

4.3. Discussion

The statistically significant variables for rate of perceived risk and likelihood of being involved in a crash were identified separately, and in general, results were found consistent with both dependent variables.

4.3.1. Traffic environment factors

Traffic environment factors of bicycle type, traffic volume, intersection type, and conflict are found to affect the perceived risk of interaction between bikes and e-bikes.

Bicycle type: For bicycle type in the interaction, compared to riding a bike and encountering a bike, it is found that riding an e-bike and encountering a bike would decrease the perceived risk. However, riding a bike and encountering an e-bike shows an insignificant influence on perceived risk.

The negative effect of riding an e-bike on perceived risk is consistent with the hypothesis put forward in section 2.2.3, that cyclists riding on an e-bike would perceive less risk than riding a conventional bike in the interaction with other conventional bikes. One potential explanation could be that cyclists riding on an e-bike might feel more dominant during interactions with other conventional bikes and perceive themselves as less vulnerable compared to those riding a conventional bike. It corresponds with the study by Petzoldt et al. (2017) and Schleinitz et al. (2017) that cyclists would reach a higher speed when riding an e-bike than riding a bike. Such a fast speed may provide dominance to cyclists who ride an e-bike and have interactions with bike users. Therefore, cyclists riding an e-bike perceive less risk in bicycle interactions than those riding a bike.

However, encountering an e-bike is found insignificant to influence the perceived risk. This insignificant influence on perceived risk contradicts the study by Dozza, Schindler, et al. (2016), Huertas-Leyva et al. (2018), and Petzoldt et al. (2017) that e-bikes were more frequently involved in crashes or conflicts than conventional bikes. The reason could be that participants found quite little difference between bikes and e-bikes interacting at an intersection because typically e-bike decreases its speed at an intersection to maneuver or perform other activities to avoid collisions.

Traffic volume: Compared to off-peak hours, it is found that cyclists would perceive a higher level of risk when cycling at peak hours.

The positive effect of traffic volume is consistent with the hypothesis, that higher traffic volume would increase the perceived risk of cycling. When riding at peak hours, the traffic environment is complex and cyclists need to interact with many other cyclists, which greatly increases their perceived risk. This finding aligns with the study by Dozza and Werneke (2014) and Petzoldt et al. (2017) that the involvement of other road users caused conflicts for bike and e-bike users, and dense traffic of e-bike is found associated with crashes (Pejhan et al., 2021).

Intersection type: Compared to the 3-leg, small-size intersection, it is found that cyclists would perceive less risk when cycling at a 4-leg, large-size intersection.
The influence of intersection type is consistent with the hypothesis, that cycling at a small intersection would increase the perceived risk, as the distance among cyclists is narrow at the small intersection, increasing the probability of collisions. This finding corresponds with the study by Vlakveld et al. (2021) that the high crash risk is associated with the proximity of bicycles.
On the other hand, a 4-leg, large-size intersection contains traffic from various directions, therefore the content is more complex than a 3-leg, small-size intersection. It is counter-intuitive that cyclists perceived less risk at the 4-leg intersection. It can be explained by risk-compensating behaviors that cyclists riding in a complex environment would pay more attention to their riding and thus compensate to perceive less risk (Noland, 1995).

Conflict: Compared to having conflicts with cyclists turning left to the opposite direction when crossing the intersection, it is found that the conflict of right turning to the same direction was associated with lower perceived risk.
The variation between the influence of conflict type could be explained by the cycling direction. In the left turn-crossing conflict, the encountering cyclist rides in the opposite direction of the participant after turning left, the distance between these two cyclists is close. While in the right turn-crossing conflict, the encountering cyclist rides in the same direction, and the distance is far. It also aligns with the study that the proximity of bicycles is associated with high crash risk (Vlakveld et al., 2021). The result shows that the left turn-crossing conflict would increase the perceived risk of bike interactions.

4.3.2. Individual factors

Individual factors of the number of crashes, preference to use an e-bike for daily cycling, the competence of cycling skills, and age are found to affect the perceived risk of interaction between bikes and e-bikes.

Number of crashes: The number of previous cycling crashes is found to positively affect perceived risk. It is consistent with the hypothesis that cyclists with crash experience would perceive a high level of risk (Schepers et al., 2020). The result shows a trend that the higher the number of crashes cyclists have, the higher the level of risk they perceive.

Preference to use an e-bike for daily cycling: A similar positive influence is found in the preference to use an e-bike for daily cycling, that more preference to use an e-bike is associated with a higher level of perceived risk. One possible reason could be that cyclists who feel vulnerable in cycling and tend to perceive high risk would prefer to use an e-bike, as e-bikes may provide dominance in interactions with conventional bikes.

Competence of cycling skills: The competence of cycling skills is found to negatively influence the perceived risk, which is consistent with the hypothesis that cyclists with high competence of cycling skills would perceive less risk of cycling (Chaurand & Delhomme, 2013).

Age: The exception is the variable of age, which is found a negative effect only on the likelihood of being involved in a crash, while the influence of age is found to be insignificant in the rate of perceived risk. This negative effect is counter-intuitive, as old age is found associated with high perceived risk in several studies (Haustein & Møller, 2016; Useche et al., 2018). However, participants of this research are mainly aged between 18 to 30. The negative effect of age could be understood that inside this younger age group, cyclists with older age have more cycling experience, so that would have lower perceived risk. This reflection corresponds with the study by (Haustein & Møller, 2016; Washington et al., 2012) that the experience of cycling is negatively associated with the perceived risk.

4.3.3. Insignificant variables

In the final results, all variables of traffic environment factors are significant, while several variables of individual factors are found insignificant to influence the perceived risk of cycling: gender, education, motivation for cycling, weekly cycling hours, expectancy on e-bike safety, and risky cycling behaviors.

The gender and educational background are found to have no effects on the perceived risk. It does not align with the hypothesis that females tend to perceive higher risk than males (Haustein & Møller, 2016; Useche et al., 2018).

The motivation for cycling is also found to have no influence on the perceived risk. One reason could be that participants were asked about their primary motivation to ride a bike/e-bike, however, in the survey they were given several hypothetical traffic scenarios to perceive risk, and these traffic scenarios have no relationship with cycling motivation.

It is expected that cyclists with more experience in cycling would perceive less risk (Haustein & Møller, 2016; Washington et al., 2012). While in the results this variable of experience is found to have no effect on the perceived risk. The experience of cycling is measured by the average weekly cycling hours, and a significant difference is found that the group of bike users have fewer cycling hours than the group of e-bike users. However, this variation in cycling hours does not reflect the effect on the perceived risk. In this study, the cycling hours are collected from self-reported information and therefore may have a bias of the real situation that cyclists may overestimate or underestimate their average weekly riding hours. Moreover, it is possible that cyclists who ride for a long period still perceive high risk in interactions with other bicycles, especially for those who previously had several crashes (Schepers et al., 2020).

The expectancy on e-bike safety and cycling behaviors show no significant influence on perceived risk, which contradicts the hypotheses. It is expected that cyclists who believe riding an e-bike is riskier than riding a bike will perceive high risk in interaction with e-bikes, and cyclists who perform erroneous cycling behaviors tend to perceive low risk. However, the results do not support these hypotheses, which might be caused by the imbalanced distribution of responses as illustrated in Fig 4.2 - Fig 4.7. The majority of cyclists agree with the opinion that riding an e-bike is dangerous and risky, and they seldom perform erroneous cycling behaviors, while only a few disagree that riding an e-bike is dangerous, and participants of this research merely perform erroneous behaviors. Therefore, such imbalanced distributions may contribute to the failure to examine these variables of effects on perceived risk.

4.3.4. Perceived risk measurement

When comparing the model of the rate of perceived risk and likelihood of being involved in a crash, an interesting variation of traffic environment and individual factors has been observed. The variables of traffic environment factors have a greater absolute value of coefficients in the model of the rate of perceived risk, while the variables of individual factors have a greater absolute value of coefficients in the model of the likelihood of being involved in a crash.
Such a difference reflects the variation of different perceived risk measurements. To measure the perceived risk, it is found that variables of traffic environment have a stronger influence on rating the perceived risk, while individual factors have a stronger influence on predicting the

likelihood of being involved in a crash. It could be explained that asking participants to rate the perceived risk with a 5-point scale is a more objective behavior, therefore the objective factors of the traffic environment play a critical role in rating perceived risk. While asking about the likelihood of being involved in a crash is more subjective and internal, participants would reflect more on personal information. Therefore individual factors play a critical role in predicting the likelihood of having crashes.

5
Conclusion

This research aims to investigate cyclists' perceived risk during the interaction between bikes and e-bikes. To enhance the comprehension of participants, traffic scenarios are presented with pre-recorded videos of cycling on a bike and an e-bike from a first-person view. Based on pre-recorded videos, an online survey was conducted to collect data on perceived risk and personal information. Then the random-effects logit model is used to explore the relationship between the traffic environment, individual factors, and the perceived risk. Eventually, the effects of influencing variables are interpreted and discussed from the model results.

5.1. Answer to research questions

Based on the results and discussion, research questions are answered as follows.

RQ1: How do cyclists perceive risk when interacting with different types of bicycles?
Specifically, three interactions are explored:

1. riding a bike, encountering a bike;
2. riding a bike, encountering an e-bike;
3. riding an e-bike, encountering a bike

The baseline of bicycle interactions is riding on a conventional bike and encountering a conventional bike. Two other interactions are compared with the baseline, one is encountering an e-bike and the other is riding on an e-bike. The results show that compared to interactions between conventional bikes, riding an e-bike and encountering a bike would decrease perceived

risk. However, no significant difference between encountering an e-bike and encountering a bike is found, indicating an insignificant effect on the perceived risk.
This finding suggests that e-bikes may have an effect on how cyclists perceive risk in bicycle interactions, especially when riding on an e-bike cyclists tend to perceive less risk compared to riding a conventional bike. However, this effect is not strong enough to significantly differentiate between encountering e-bikes and conventional bikes. It highlights the complexity of factors influencing perceived risk in such interactions and provides insights into the dynamics of e-bike use in mixed bicycle environments.

RQ2: How do traffic environment factors influence cyclists‘ perceived risk when they are interacting with other cyclists?
Traffic environment factors of traffic volume, intersection type, and conflict type are explored on the impacts of perceived risk in bike interactions.
It is found that cycling at peak hours with a lot of other cyclists would increase the perceived risk, indicating that higher traffic volume would cause higher perceived risk. This implies that crowded cycling conditions may make cyclists feel less safe or more vulnerable, therefore highlighting the importance of managing and improving safety measures in high-traffic cycling environments.
The intersection type is found associated with the perceived risk that riding at a large intersection decreases cyclists‘ perceived risk. This suggests that cyclists may feel safer at larger intersections, possibly due to better visibility and more space to avoid collisions. It highlights the significance of intersection design and management in promoting cyclist safety.
And having a conflict with left-turning cyclists is found to increase the perceived risk. Cyclists may need to be particularly cautious and aware when navigating intersections or situations involving left-turning cyclists.

RQ3: How do individual factors influence cyclists‘ perceived risk when they are interacting with other cyclists?
Various individual factors are explored in terms of demographics, motivation for cycling, weekly cycling hours, number of crashes, expectancy on e-bike safety, competence of cycling skills, and cycling behaviors.
The number of crashes is found positively related to perceived risk and suggests that cyclists who have experienced more crashes tend to perceive their cycling environment as riskier. This finding highlights the potential impact of personal safety experiences on their perception of risk and indicates the importance of improving safety measures and education to reduce

the occurrence of cycling accidents.

A similar positive effect is found in preference to use an e-bike. It indicates that individuals who prefer using e-bikes may perceive higher levels of risk when cycling. This could be due to concerns about e-bike safety or unfamiliarity with e-bike use. It suggests the need for education and safety measures to address these concerns and promote the adoption of e-bikes.

While competence of cycling skills is found a negative influence on perceived risk. This finding suggests that individuals who are more confident in their cycling abilities tend to perceive lower levels of risk. This highlights the importance of cycling skill development and training in improving cyclists' confidence and reducing their perception of risk.

Age is found only negatively related to predicting the likelihood of being involved in a crash, while no significant effect of age is found in the rate of perceived risk. This variation in different perceived risk measurements suggests that older cyclists tend to predict less likelihood of having crashes, however, their ratings on perceived risk may not necessarily decrease as a result.

Besides, gender, education, motivation for cycling, weekly cycling hours, expectancy on e-bike safety, and cycling behaviors are found insignificant effects on the perceived risk. This suggests that these factors may not significantly influence how cyclists perceive the overall risk associated with cycling in this specific context.

Perceived risk measurement

Apart from the answers to research questions, an interesting variation of perceived risk measurement is found in the influence of different factors.

The measurement of rate of perceived risk is more objective, as participants are asked to provide a rating on a scale. In this case, factors related to the traffic environment, which are external and observable, play a critical role in shaping participants' perceptions of risk. On the other hand, the measurement of the likelihood of being involved in a crash is more subjective and internal, as it involves participants reflecting on their own likelihood of experiencing a crash. In this context, individual factors have a stronger influence on participants' predictions about their own crash risk.

These findings suggest that the way perceived risk is measured can lead to variations in the importance of different factors. When participants rate perceived risk on a scale, external factors related to the traffic environment are prominent. In contrast, when participants predict the likelihood of being in a crash, personal factors and experiences become more significant. These insights provide a nuanced understanding of how individuals assess and perceive risk in cycling contexts.

5.2. Societal Contributions

The results of this thesis offer valuable insights into various factors affecting perceived risk in bicycle interactions, contributing to the enhancement of cycling safety management and the promotion of societal benefits.

From the perspective of e-bike usage, the findings indicate that riding on an e-bike can reduce perceived risk. However, no significant impact is observed when encountering an e-bike as compared to encountering a conventional bike. These results shed light on the influence of e-bikes on cyclists' perceived risk and underscore the complexity of interactions between conventional and e-bike users in shared cycling spaces.

Considering the traffic environment, factors such as traffic volume, intersection type, and conflict type are found to influence cyclists' perceived risk. These findings underscore the significance of effective traffic management and safety measures, particularly in crowded bicycle traffic during peak hours and at smaller intersections. Additionally, they emphasize the importance of cyclist awareness and caution, especially in situations involving left-turning and crossing conflicts.

Examining various individual factors, the findings emphasize the potential for interventions and education to reduce perceived risk and enhance cycling safety. By implementing improved safety measures, promoting responsible cycling behaviors, and enhancing education, society can work towards reducing cycling accidents and lowering the perceived risk associated with cycling. Notably, tailored educational initiatives and safety measures for e-bike users are needed to address their specific concerns and encourage the safe adoption of e-bikes as a sustainable mode of transportation. Furthermore, investing in training and education to enhance cycling skills can boost cyclists' confidence and positively impact overall cycling safety.

5.3. Limitations and recommendation for future research

5.3.1. Theoretical limitation

Conceptual framework:

The study has relied on a limited conceptual framework. A more comprehensive theoretical foundation could have enhanced the study's explanatory power, such as considering the Theory of Planned Behavior, or the Unified Theory of Acceptance and Use of Technology (UTAUT). Moreover, by using these theories, the decision-making and cycling behaviors could be evaluated after examining the perceived risk, to gain a more comprehensive insight into bicycle safety issues.

The study might not have fully considered broader contextual factors, such as other types of cycling infrastructure except for intersections, traffic regulations, or cultural norms, which can have a profound influence on risk perception.

Survey recruitment:
The survey was distributed mostly among university students and in the Netherlands, therefore the sample of cyclists lacks diversity, and this research does not capture cultural differences, which can lead to variations in how individuals perceive and respond to risk.
Data analysis:
This research treats individual factors and traffic environmental factors as isolated entities. In reality, these factors often interact in complex ways that may not be fully captured by the random-effects ordered logit model. Besides, the unobserved factors across observations are neglected in the model, in the future, this can be captured by estimating a random parameter ordered logit model or latent class ordered logit model.

5.3.2. Methodology limitation

One notable limitation of this research pertains to the methodology employed in measuring perceived risk. The primary data collection method involved the use of surveys, which relied on self-reported information from participants. While surveys are a commonly used tool for assessing subjective experiences, they do have inherent limitations. Self-reported data may be subject to biases and inaccuracies, as individuals may not always accurately represent their perceptions or their responses may be influenced by various factors, including social desirability bias or recall bias. In future research, it would be beneficial to complement self-reported data with physiological measures as an additional reflection of perceived risk. For instance, monitoring participants' heart rates during cycling scenarios could provide objective physiological data that aligns with their perceived risk levels, offering a more comprehensive perspective on their emotional and physiological responses.

Another noteworthy limitation of the current study pertains to the presentation of traffic scenarios. The research utilized pre-recorded videos to simulate cycling environments and elicit responses from participants. While these videos can provide some level of stimuli and context, they inherently lack the immersive qualities and sensory feedback associated with real-life cycling experiences. To address this limitation, future research endeavors could explore alternative methods for presenting traffic scenarios or measuring perceived risk in a more realistic and ecologically valid manner. For instance, the use of cycling simulators or the implementation of naturalistic experiments involving actual cycling in real-world traffic conditions could provide a closer approximation of the feelings and risk perceptions that cyclists encounter in their day-to-day experiences. Such approaches would help bridge the gap between laboratory settings and real-world cycling situations, enhancing the validity and applicability of the research findings.

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A

Correlation matrix

Table A.1: Correlation matrix for explanatory variables

	Bike type	Traffic volume	Intersect-ion type	Conflict	Age
Bike type	1.00				
Traffic volume	0.00	1.00			
Intersection type	0.03	0.00	1.00		
Conflict	0.00	0.00	0.00	1.00	
Age	0.00	0.00	0.00	0.00	1.00
Gender	0.00	0.00	0.00	0.00	-0.01
Education	0.00	0.00	0.00	0.00	0.0639*
Type of cyclist	0.00	0.00	0.00	0.00	0.1691*
Motivation for cycling	0.00	0.00	0.00	0.00	0.0882*
Weekly riding hours	0.00	0.00	0.00	0.00	-0.1020*
Number of crashes	0.00	0.00	0.00	0.00	-0.1793*
Expectancy1	0.00	0.00	0.00	0.00	0.1753*
Expectancy2	0.00	0.00	0.00	0.00	0.00

Expectancy3	0.00	0.00	0.00	0.00	0.05
Expectancy4	0.00	0.00	0.00	0.00	0.0853*
Cycling behaviors1	0.00	0.00	0.00	0.00	-0.0883*
Cycling behaviors2	0.00	0.00	0.00	0.00	-0.0870*
Cycling behaviors3	0.00	0.00	0.00	0.00	-0.0666*
Competence1	0.00	0.00	0.00	0.00	-0.05
Competence2	0.00	0.00	0.00	0.00	-0.0639*
Competence3	0.00	0.00	0.00	0.00	0.0969*

	Gender	Education	Type of cyclist	Motivation for cycling	Weekly riding hours
Gender	1.00				
Education	0.2276*	1.00			
Type of cyclist	-0.0688*	-0.1789*	1.00		
Motivation for cycling	-0.1325*	-0.1162*	-0.03	1.00	
Weekly riding hours	0.05	-0.1126*	0.2460*	-0.0755*	1.00
Number of crashes	0.1078*	0.03	-0.0679*	-0.1823*	0.2874*
Expectancy1	0.00	0.0616*	0.02	-0.05	-0.1270*
Expectancy2	0.1085*	-0.01	0.1562*	0.00	-0.0716*
Expectancy3	0.0835*	-0.03	-0.06	-0.0861*	-0.1184*
Expectancy4	-0.01	0.05	-0.0718*	-0.0960*	-0.1463*
Cycling behaviors1	-0.0650*	0.0724*	-0.03	0.0714*	0.1610*
Cycling behaviors2	0.01	-0.0960*	-0.01	0.0853*	0.2220*
Cycling behaviors3	-0.0863*	-0.04	0.0801*	-0.04	0.1986*
Competence1	-0.1670*	-0.0749*	-0.03	-0.04	0.2092*

Competence2	-0.1099*	-0.1272*	0.02	0.0813*	0.2384*
Competence3	-0.1665*	-0.1755*	0.03	-0.05	0.0702*

	Number of crashes	Expectancy1	Expectancy2	Expectancy3	Expectancy4
Number of crashes	1.00				
Expectancy1	0.00	1.00			
Expectancy2	-0.03	-0.1025*	1.00		
Expectancy3	-0.02	0.7022*	-0.0988*	1.00	
Expectancy4	0.0690*	0.6650*	0.01	0.5373*	1.00
Cycling behaviors1	0.2551*	0.04	0.0618*	0.04	-0.03
Cycling behaviors2	0.1718*	0.1352*	-0.03	0.1562*	0.1935*
Cycling behaviors3	0.1083*	0.0955*	-0.0804*	0.1208*	0.0805*
Competence1	0.0797*	0.1792*	-0.02	0.2007*	0.2079*
Competence2	0.0804*	0.0891*	0.0765*	0.04	0.1760*
Competence3	0.00	0.1890*	0.04	0.2172*	0.1652*

	Cycling behaviors1	Cycling behaviors2	Cycling behaviors3	Competence1	Competence2
Cycling behaviors1	1.00				
Cycling behaviors2	0.3495*	1.00			
Cycling behaviors3	0.1974*	0.1643*	1.00		
Competence1	0.1379*	0.1833*	0.1184*	1.00	
Competence2	0.04	0.1014*	0.1323*	0.4926*	1.00
Competence3	0.0718*	0.1614*	0.1358*	0.4931*	0.5263*

	Competence3

Competence3	1.00

*correlation coefficients significant at the 5% level or better