Study of Car-Bicycle Safety at Signalized Intersections from Multi-Aspects

vorgelegt von
M.Eng.
Peipei Liu
geb. in Yantai, China

von der Fakultät V - Verkehrs- und Maschinensysteme
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Promotionsausschuss:

Vorsitzende: Prof. Dr.-Ing. Nele Rußwinkel
Gutachterin: Prof. Dr. rer. nat. Stefanie Marker
Gutachter: Dr.-Ing. Heiko Johannsen

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Abstract

Cycling is increasing in popularity in urban areas due to its individual, social and environmental benefits. However, cyclists are among the most vulnerable road users. Especially at intersections, many bicycles collide with passenger cars despite the control of traffic signals. This thesis focuses on car-bicycle safety at signalized intersections. Various factors contribute to the occurrence of road accidents, namely factors from the human, vehicle and environment aspects. The aim of this thesis is to explore potential measures to reduce car-bicycle accidents at signalized intersection from multi-aspects.

In accident prevention, one must know the world of accidents. Given that few accident analysis has specifically focused on car-bicycle accidents at signalized intersections, this thesis analyze two accident databases. The analysis deals with the characteristics of car-bicycle accidents at signalized intersections. It reveals possible accident scenarios, frequencies of each scenario and common accident causes of accidents.

Naturalistic Driving Observation (NDO) is a fast-growing method for traffic safety studies. Despite of many NDO studies, few have particularly investigated interactions between car drivers and bicyclists at signalized intersections. This thesis carries out a Quasi-NDO study in order to investigate the interactions between car drivers and cyclists at signalized intersections from perspective of car drivers. A car is instrumented with various sensors. The instrumented car is used to collect the data of driving behaviors and environment, while twenty-two participants separately drive this car in real traffic. The collected driving behaviors include dynamic driving data, drivers´ body movements and eye movements. A self-programmed Graphical User Interface and a video annotation tool are used for data analysis in order to detect car-bicycle conflicts. In addition, the collected eye movement data is analyzed in the scenario (i.e. right-hook scenario), where car turns right and bicycle goes through. With 146 detected right-hook events, the analysis reveals bicycle-scanning strategies of car drivers. According to the bicycle-scanning strategies, potential suggestions are proposed to mitigate the risk of this scenario.

Road users´ perceived risk influences individual behaviors, and therefore it plays an important role in traffic safety. Through an online survey, the perceived risk of car drivers and cyclists (no matter the consequences of the crash) are investigated for seventeen common car-bicycle scenarios at signalized intersections. A comparison between the subjective perceived risk und the objective risk shows that a discrepancy exists among both car drivers and cyclists. Moreover, it shows that cyclists tend to perceive less risk than car drivers do. The implications of these results are vital for improvement of car-bicycle safety at signalized intersections.

Safety effects of bicycle facilities are controversial, especially at intersections. By use of the Negative Binomial model, safety effects of bicycle facilities on car-bicycle crash risk at signalized intersections are estimated. The effects of other intersection factors are simultaneously considered. The estimation results shows that bicycle lanes have positive safety effects, while bicycle paths have negative safety effects.

Kurzfassung

Aufgrund seiner Vorteile für Individuum, Gesellschaft und Umweltnutzen nutzen immer mehr Menschen das Fahrrad in Innenstädten als Verkehrsmittel. Fahrradfahrer gehören jedoch zu den am meisten gefährdeten Verkehrsteilnehmern. Besonders an Knotenpunkten treten trotz der Steuerung durch Lichtsignalanlagen (LSA) zahlreiche Unfälle zwischen Pkw und Fahrrädern auf. Im Rahmen der vorliegenden Arbeit wird die Sicherheit von Pkw- und Fahrradfahrern an Knotenpunkten mit LSA fokussiert. Verschiedene Faktoren von Menschen, Fahrzeug und Umwelt könnten Verkehrsunfälle verursachen. Ziel dieser Arbeit ist, aus den diversen Aspekten mögliche Maßnahmen zur Reduzierung von Unfällen zwischen Pkw und Fahrrädern an Knotenpunkten mit LSA zu ermitteln.

Für die Unfallprävention muss man die Details der Unfälle kennen. Wegen fehlender Unfallforschung, die speziell Unfälle zwischen Pkw und Fahrrad an Kontenpunkten mit LSA betrachtet, analysiert diese Arbeit zwei Unfalldatenbanken. Diese Analyse konzentriert sich auf die Merkmale der Unfälle zwischen Pkw und Fahrrädern an Kontenpunkten mit LSA. Hierbei werden die möglichen Unfallszenarien, Häufigkeiten jedes Szenarios und häufige Unfallursachen aufgezeigt.

Naturalistic Driving Observation (NDO) ist eine stark wachsende Methode im Bereich der Verkehrssicherheit. Obwohl viele NDO-Studien durchgeführt wurden, hat keine insbesondere die Interaktionen zwischen Pkw-Fahrern und Radfahrern an Knotenpunkten mit LSA untersucht. Eine Quasi-NDO-Studie wird in dieser Arbeit durchgeführt, um aus Sicht der Pkw-Fahrer die Interaktionen zwischen Pkw- und Radfahrern an Knotenpunkten mit LSA zu untersuchen. Ein Auto wird mit verschiedenen Sensoren ausgerüstet. Mit diesem Auto werden die Fahrerverhaltens- und Umgebungsdaten von 22 Teilnehmern im Realverkehr erhoben. Die aufgezeichneten Fahrerverhaltensdaten enthalten dynamische Fahrdaten, Köperbewegungen und Augenbewegungen der Fahrer. Eine selbstprogrammierte grafische Benutzeroberfläche und eine Software zur Videoannotation werden zur Datenanalyse verwendet, um Konflikte zwischen Pkw und Fahrrad zu identifizieren. Zusätzlich werden die erhobenen Augenbewegungsdaten in dem Szenario bzw. Rechtsabbiege-Szenario analysiert, in dem der Pkw rechts abbiegt und das Fahrrad geradeaus fährt. Mit 146 erkannten Rechtsabbiege-Ereignissen zeigt diese Analyse auf, wie die Pkw-Fahrer die Radfahrer erkennen. Basierend auf diesen Fahrrad-Scan-Strategien werden Möglichkeiten zur Verringerung des Risikos in dem Szenario abgeleitet.

Risikowahrnehmung der Verkehrsteilnehmer beeinflusst ihr Verhalten und spielt eine wichtige Rolle für die Verkehrssicherheit. Mit Hilfe einer Online-Umfrage wird die Risikowahrnehmung der Pkw- und Radfahrer (unabhängig von den Unfallfolgen) für 17 häufige Konflikt-Szenarien zwischen Pkw und Fahrrad erforscht. Ein Vergleich zwischen dem subjektiv wahrgenommenen Risiko und dem objektiven Risiko zeigt, dass eine Diskrepanz sowohl bei Pkw-Fahrern als auch bei Radfahrern besteht. Weiterhin zeigt sich, dass Radfahrer dazu neigen, ein geringeres Risiko als Pkw-Fahrer wahrzunehmen. Diese Ergebnisse sind für die Verbesserung der Sicherheit von Pkw- und Fahrradfahrern an Knotenpunkten mit LSA von großer Bedeutung.

Es ist umstritten, wie Radverkehrsanlagen vor allem an Knotenpunkten die Verkehrssicherheit beeinflussen. Mittels des negativen Binomialmodells werden die Auswirkungen von Radstreifen und Radwegen auf Pkw-

Fahrrad-Unfallrisiko an Knotenpunkten mit LSA beurteilt. Dabei werden auch die Auswirkungen anderer Kreuzungsfaktoren berücksichtigt. Radstreifen gehen den Ergebnissen zufolge mit einem positiven Sicherheitseffekt einher, während Radwege eher negative Auswirkungen auf die Sicherheit haben.

Table of Contents

1. Motivation and thesis structure

1.1. Motivation: cycling safety at signalized intersections

Cycling, recognized as an excellent transport mode, is beneficial to the individual, environment and society. For individuals, cycling is a cheap form of transport, and is proven to be a physical activity that has positive influence on health and fitness [1]. Cycling is sometimes more efficient than other transport modes in urban areas by allowing bicyclists to avoid traffic jams. Environment and society benefit from the fact that cycling helps to develop more sustainable transportation. It decreases air pollution, green house gas emissions and noise pollution, enhances major public-health and requires only cheap infrastructure [2,3].

For these reasons, cycling has attracted increasing attention in European, American, and Australian major cities over the last two decades [4]. Figure 1-1 presents bicycle modal shares for all journeys per country. The Netherlands have the highest bicycle modal share with 26%, followed by Denmark with 19% and Germany with 10% [5]. The three European countries are among the most successful countries at promoting cycling for daily trips. The thriving of cycling in the three countries depends on the bicycle-friendly policies and good weather conditions. The national and local policy-makers have implemented a series of measures to make cycling safer, more convenient and more attractive. These measures include improvement of bicycle infrastructure (e.g. construction of separated bicycle facilities and parking facilities), promotion of inter-modality for cyclists, organization of traffic education and training programs as well as introduction of bicycle sharing system [6]. Compared to European countries, cycling levels in Canada, the USA and Australia are far lower with bicycle use shares of 2%, 1% and 1%, respectively [7,8]. Due to the values of cycling being recognized, these countries have started to develop cycling plans and strategies to promote cycling mobility, learning from European successful practices. It is predictable that more people will cycle for commuting as well as for leisure and tourism.

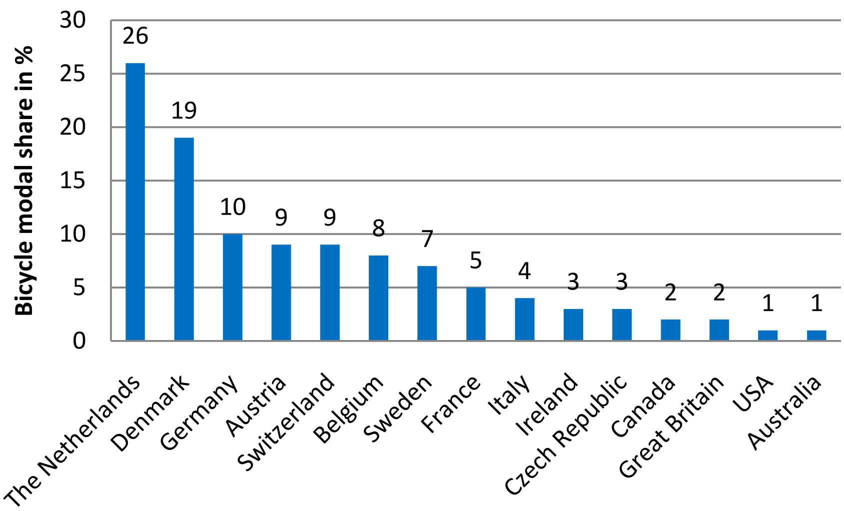


Figure 1-1 Bicycle modal shares for all journeys per country (self-built figure according to bicycle share data of European countries in 2006 [5], Canada in 2006 [7], USA in 2009 [7], and Australia in 2006 [8])

Along with the benefits and popularity of cycling, cycling features a critical merit of safety. Cyclists are among the most vulnerable road users due to the characteristics and nature of cycling. Cyclists often share roads with motorized vehicles, resulting in potential collisions. If a collision between cyclists and vehicles sharing the road happens, the kinetic energy of vehicles is impressive, and cyclists have no outer protective cells. In summary, the vulnerability of cyclists is reflected both in terms of the probability of being involved in a crash, and the possible consequences that result from a crash [9].

To improve cycling safety, European countries have adopted a number of measures, e.g. extensive system of separate cycling facilities, intersection modifications, priority traffic signals, bicycle-friendly traffic laws and enhanced traffic education and training for cyclists and motorists [10]. The measures have indeed played an effective role in promoting safer cycling. While the number of all road fatalities in the EU is decreasing every year, the downward trend in the number of fatalities among cyclists is also observable. Figure 1-2 shows the number of cyclist fatalities and the proportion among total road fatalities in the EU between 2004 and 2013, indicating a decrease in the number of cyclist facilities by 32%. However, this figure also clearly shows the proportion of cyclist fatalities among all road fatalities is increasing. In other words, the trend for cyclists is not decreasing at the same rate as for all road fatalities. This trend is believed to be the result of the strongly increasing popularity of cycling and the consequently increasing number of cyclists in Europe [6]. Of all traffic fatalities, the average proportion of cyclist fatalities makes up 7.8% in the EU counties in 2013. In countries like the Netherlands, Denmark and Germany, where cycling is an important daily mode of transport and safer cycling environment is provided, the proportion of cyclist fatalities is even higher, up to 23.5%, 17.3% and 10.6% respectively [11]. These data suggests that more efforts are needed to improve the cycling safety.

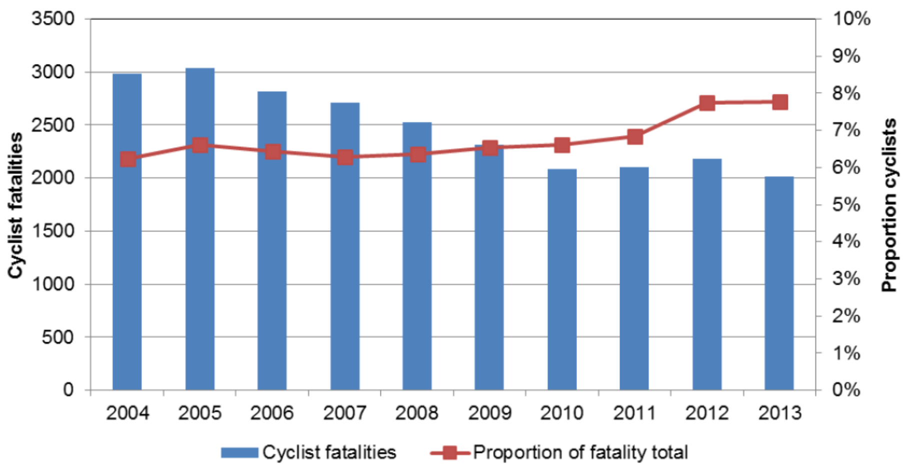


Figure 1-2 Number of cyclist fatalities and proportion among all road fatalities in EU 2004-2013 [12]

Germany is one of the top three European countries in terms of bicycle use. The issue of cyclist safety in traffic deserves more attention. In 2014, an amount of 78,296 cyclists was involved in road accidents with injuries or fatalities in the whole country [13]. Among them, 354 death and 13,206 severely injured. They accounted for 11.7% of total road fatalities and 21.4% of severe road injuries. Looking back at bicycle-accident records in this country from 2001 to 2014 as shown in Figure 1-3, no decrease can be observed in the total number of cyclist injuries [14]. Although the number of cyclist fatalities decreased in recent years as shown in Figure 1-3, the proportion among all road fatalities is in a trend of increase, similar to the status in the entire EU as shown in Figure 1-2.

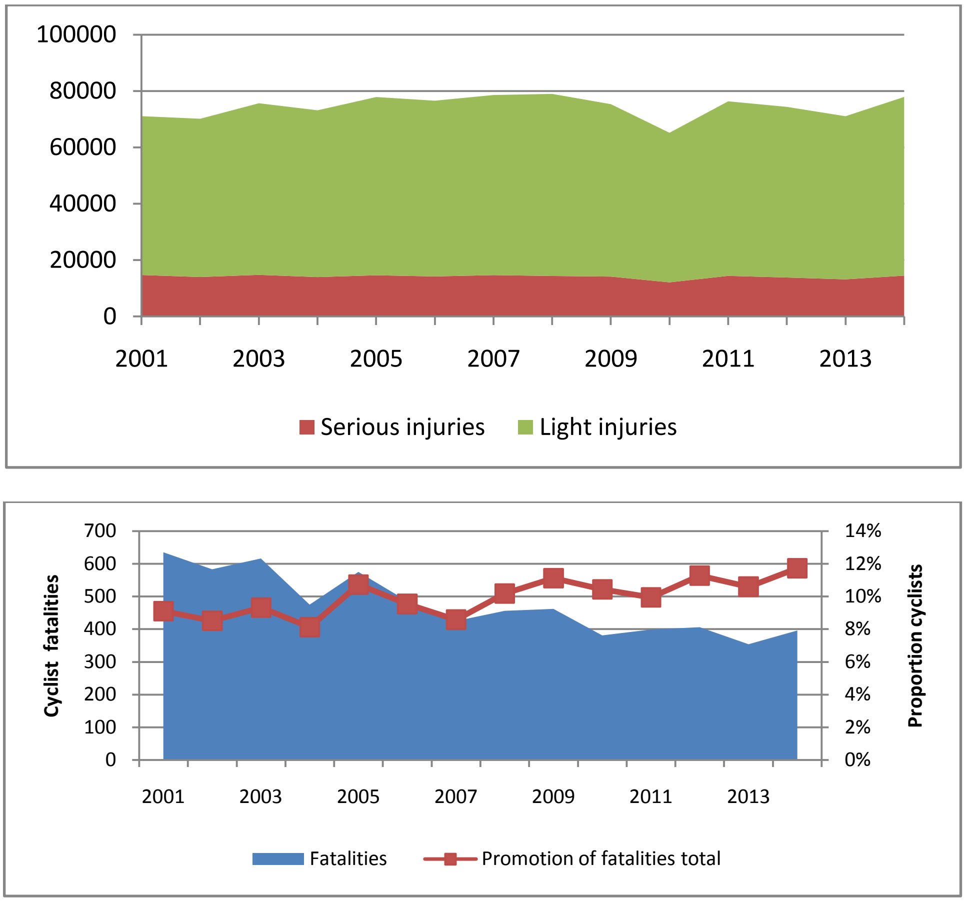


Figure 1-3 Number of cyclist injuries (top), and number and proportion of fatalities (bottom) in Germany from 2001 to 2014 (self-made figure according to [14])

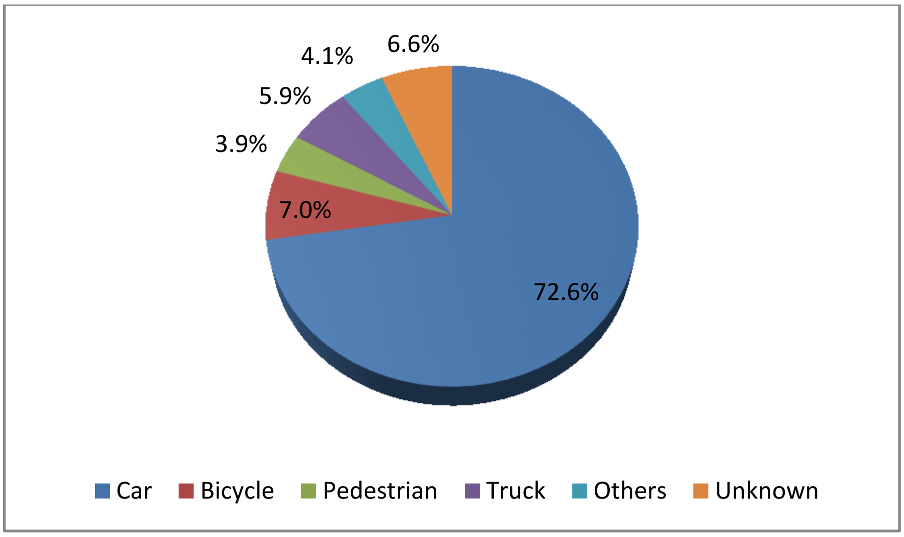


Figure 1-4 Collision partner distribution of bicycle-accidents in Berlin from 2004 to 2008 (self-made figure according to [15])

In bicycle accidents, bicycles may collide with different modes of transport, such as cars, trucks, pedestrians and other bicycles. Cars were the most frequent collision partners. In Berlin from 2004 to 2008, 33,766 bicycle-accidents (even without injuries) were registered by the Berlin Police [15]. The collision partner distribution in these bicycle-accidents is presented in Figure 1-4. Bicycles collided with cars in 72% of bicycle-accidents. The reason is that passenger cars are the most widely used mode of transport that share roads with bicycles.

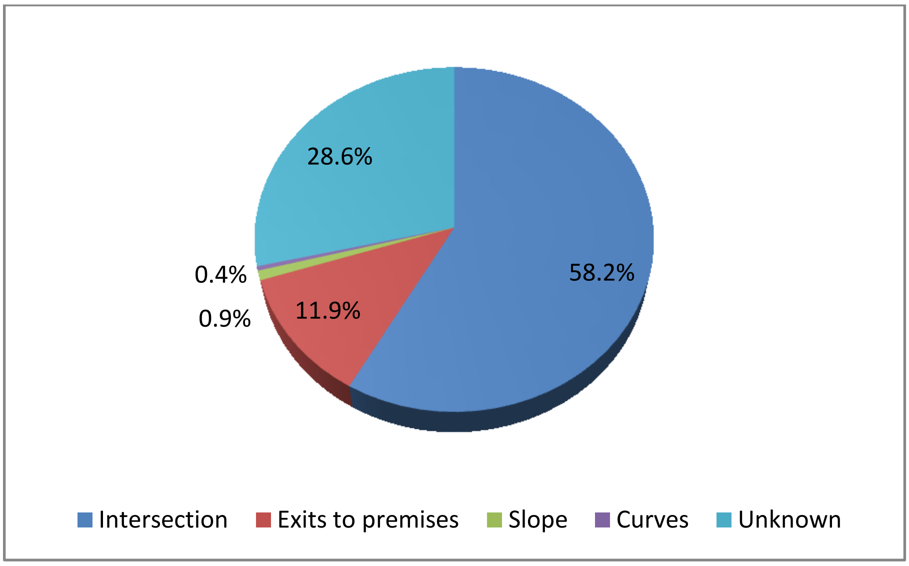


Figure 1-5 Road location distribution of bicycle-accidents in Berlin from 2004 to 2008 (self-made figure according to [16])

Concerning accident locations, intersections are undoubtedly among the most dangerous road locations for bicycles. The analysis of bicycle-accidents in Berlin from 2004 to 2008 indicates that 58.2% of bicycle accidents took place at intersections, as shown in Figure 1-5 [16]. Intersections could be also classified according to the types of control types. The common intersection control types are the basic rules of road, yield or stop signs and traffic signals [17]. Traffic signals, as the ultimate form of traffic control, can generally avoid some conflicts, and therefore substantially decrease bicycle accidents. However, a considerable number of accidents occurred at intersections controlled by traffic signals, known as signalized intersections. Statistic shows that up to 22.4% of bicycle accidents occurred at signalized intersections in Berlin in 2013, accounting for nearly half of bicycle accidents at intersections [18]. On the one hand, accidents might happen due to red-light violation, and rear-end accidents might happen due to the phenomenon of amber dilemma [17,19,20]. On the other hand, not all conflicts could be avoided under the control of traffic signals, even if road users obey the signal indication. Development of some conflicts is depending on the interpretation of the right of way rule. Road users need to evaluate traffic conditions and negotiate with each other to avoid accidents, if they have to cross each other. The extra requirements of human efforts often result in accidents.

The cycling safety issue has different features in collisions with different types of road users and at different road locations, such as collision types, frequency, causation, consequences, etc. In this work, focus is specially on cycling safety concerning cars, who are the most frequent collision partners in bicycle accidents, at signalized intersections, where road users are controlled in the highest level, and however, still a considerable number of bicycle accidents occur.

1.2. Motivation: study from multi-aspects

The aim of this thesis is to explore possible implications and countermeasures to decrease car-bicycle accidents at signalized intersections. According to the General Systems Theory, the complex and dynamic process in road traffic system is described as the interactions and relationships among road users, vehicles and environment [21]. An accident happens, when the interactions between the components in the road traffic system is inappropriate or unsafe. In other words, road accidents are viewed as failures of the human-vehicle-road system rather than failure of any single components. Similar to the General Systems Theory, human, vehicles and infrastructure are considered the three main causes of road traffic accidents in the principle of triple E, namely Education, Enforcement and Engineering [22]. A large number of accident investigation studies provide pictures of accidents causes. For example, Figure 1-6 shows the varied contribution strengths of three factors in the traffic system.

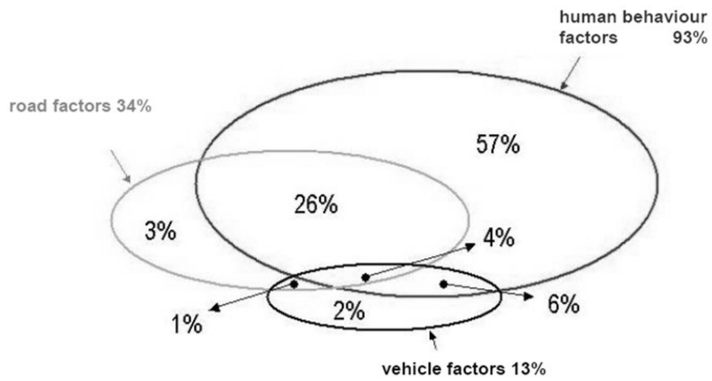


Figure 1-6 Distribution of accident contribution factors [23]

Under the guidance of the General systems Theory and the principle of triple E, a multi-disciplinary study is applied to resolve the problems of car-bicycle safety at signalized intersections. That is to find out possibilities to improve the safety from multi-aspects by looking into the elementary components in road traffic system.

In accident prevention, an important step is to know the world of accidents. Accident data analysis is the traditional way to address traffic safety. Accident analysis can generally tell what types of accidents happen, how often they happen and what the accident consequences are. The official national accidents registered by the police are the main information source for accident analysis. In-depth accidents are another essential source for improving traffic safety. They could provide extensive data in a wide range of fields before, after and at that moment of crashes. As the foundational work in safety study, accident data could be analyzed to investigate the characteristics of car-bicycle accidents at signalized intersections.

The method to understand the underlying causes of accidents based on historical accident data analysis has limitations. For example, accidents are rare events; accident data lacks detailed information on the chain of events preceding an accident [24,25]. Traffic conflicts are an effective surrogate for accident data analysis for safety diagnosis [26]. The traditional way to collect traffic conflicts relies on human observation by on-site observation [27]. This way is challenged on issues regarding the repeatability and consistency of results. Moreover, this kind of observation is restrained in limited locations, making the results sensitive to site-specific factors. Overcoming these shortcomings of conflict collection by the traditional way, Naturalistic Driving Observation (NDO) that combines cameras, radars, eye-tracking devices and other sensors is becoming a new promising approach to capture, store and analyze traffic conflicts [26,28]. In conflicts collected by use of NDO, the behavioral and situational aspects that are not covered in accident data could be recorded and analyzed. In this way, car-bicycle safety at signalized intersections could be investigated from the human aspect, i.e. behaviors of road users.

At signalized intersections, bicycles collide with cars in different scenarios, with regard to movement directions of road users, their relative location and road layouts. Due to different collision mechanisms that underlie an accident scenario, accidents of different scenarios occur with different frequencies. Car-bicycle accident analysis could reveal the real frequencies of each accident scenario, measuring the objective risk. According to the driving behavior models of Klebelsberg [29], it is an ideal situation for safety when road users maintain a stable balance between subjective perceived risk and objective safety. It is stated that dangerous situations might emerge, if the subjective safety is higher than the objective safety. When people underestimate risk in a given situation, they are more likely to adopt risky behaviors and therefore to be involved in crashes. Road users´ subjective perceived risk of car-bicycle accidents scenarios at signalized intersections is still largely unexplored. The present work could therefore address if and how far the subjective perceived risk deviates from the objective risk. Any discrepancy between them might play a role in crash occurrence. Such a study is investigating car-bicycle safety at signalized intersections also from the human aspect, i.e. risk perception.

Bicycle facilities are one of most important bicycle-specific bicycle infrastructures to promote cycling. However, their effects on cycling safety are controversial especially at intersections [30]. It is argued that the most probable explanation for the confusion on the safety effects of bicycle facilities is that the safety effects of bicycle facilities depend very much on the context into which they are introduced [31]. That is, the safety effects of bicycle facilities should be investigated while simultaneously considering factors to describe the bicycle facility context, such as the traffic mode volume, geometric design and other road infrastructures. The frequent methods for the safety effects of bicycle facilities are the before-after study and the case-control study. The two methods have their own limitations in considering a combined set of intersection factors. Most of the before-after studies only controlled for the bicycle traffic volume, while in case-control studies, only a limited number of factors were controlled for in selecting a comparison group (the first-stage study in [32]), or only a very small sample were available when too many factors were controlled for [33]. Accident Prediction Models (AMPs), which are multivariable formulas to describe the statistical relationship between the safety level of roads and road factors, allow for investigation of safety effects of bicycle facilities combining the effects of other intersection factors. Such a study by use of AMP is considering car-bicycle safety at signalized intersections from the environmental/infrastructural aspect.

1.3. Thesis structure

This thesis is to look into the three elementary components in road traffic system, namely human, infrastructural and vehicular factors, and their interactions, which are all potential factors resulting in occurrence of car-bicycle accidents at signalized intersections. To explore possible implications and countermeasures to decrease car-bicycle accidents at signalized intersections, different methodologies are employed.

In Chapter 2, the current state of scientific and technological knowledge concerning road traffic safety, especially concerning safety issues between cars and bicycles at signalized intersections, are discussed.

Historical accidents between cars and bicycles at signalized intersections are analyzed to understand their characteristics, including car-bicycle accident scenarios, frequency of different scenarios and accident causes. The analyzed accident databases include the accidents registered by the Police in Berlin, which is a typical bicycle city and the German In-Depth Accident Study (GIDAS) accident data that is regarded as being representative for German. This part of work is described in Chapter 3.

An instrumented car records car drivers´ driving behaviors, including driving dynamic behaviors, body movements, eye movements and the environment. From the collected data, car-bicycle conflicts are detected and analyzed, aiming to investigate interactions between car drivers and cyclists at signalized intersections. In addition, eye movement data is analyzed to investigate how car drivers visually detect and observe bicyclists in the most frequent car-bicycle scenario. This work is presented in Chapter 4.

An online-survey is carried out to gather risk perception of road users in seventeen selected car-bicycle accident scenarios at signalized intersections. The aim is to examine if they could accurately evaluate the risk in these scenarios. Chapter 5 introduces the online-survey, statistical analysis and results.

A suitable Accident Prediction Model (AMP) is selected to assess safety effects of bicycle facilities at signalized intersections. Bicycle facilities as well as variables related to intersection design are selected and put into the assessment. The effect coefficients of each selected variables are obtained, indicating the effects of each variables: negative or positive. The applied model, considered intersection factors and resulting effect coefficients are represented in Chapter 6.

In Chapter 7, results from different aspects are integrated to discuss comprehensively the safety issues between cars and bicycles at signalized intersections. Appropriate countermeasures for safety improvements are proposed.

Figure 1-7 illustrates the structure of the work in this thesis.

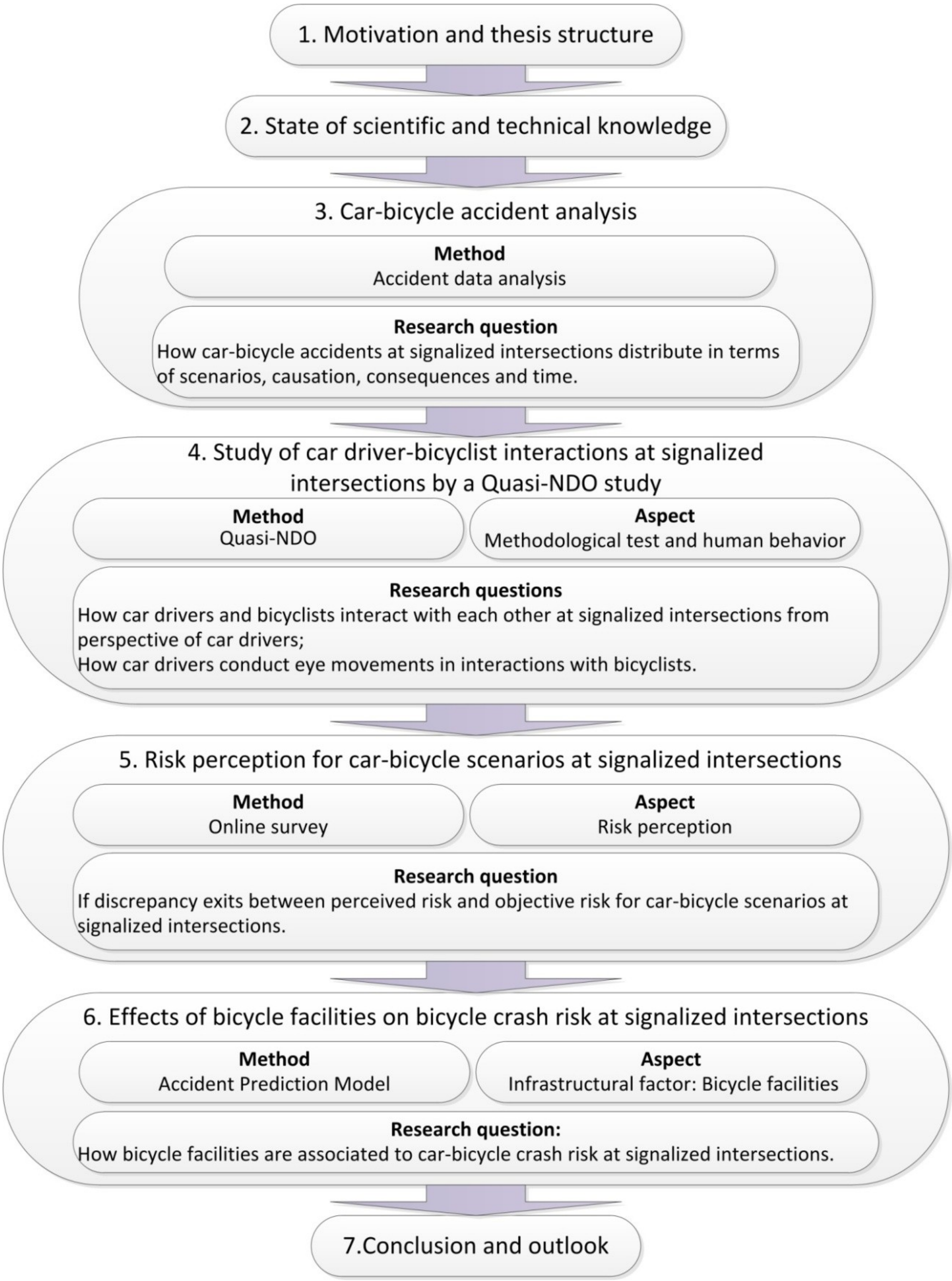


Figure 1-7 Thesis structure

2. State of scientific and technical knowledge

This chapter introduces the methodologies and terminologies of road safety used in this thesis. The methodologies include historical accident data analysis, in-depth accident analysis, Traffic Conflict Techniques (TCT), Naturalistic Driving Observation (NDO), and Accident Prediction Models (APM). The terminologies involve eye-tracking and perceived risk perception. The introduction focuses mainly on the scientific and technical knowledge concerning these methodologies and terminologies, their advantages and disadvantages and their application.

2.1. Historical accident data analysis

The traditional way to measure traffic safety depends on accident data analysis. It concerns with the number of traffic accidents and their consequences. Accident data is believed to be able to build a foundation for traffic safety based on a logical assumption "that history repeats itself and that circumstances which cause one accident may well cause another" [34]. The approach based on historical accident data is proven useful to generally evaluate traffic safety and identify specific traffic safety problems.

There are several accident data sources for traffic safety research. The official national accidents registered by the police are the main information source. Insurance company data and hospital data are often only used as additional sources. However, the police accident data is not set up entirely for traffic safety purpose. Thus, there are availability and quality problems when approaching to traffic safety by accident data analysis. The problems have been discussed in several studies [24,25] and can be summarized as followed:

- Accident data rarely includes detailed information on the chain of events preceding an accident, and contains mostly only the accident causes that are oriented at criminal offences and irregularities. The behavioral and situational aspects concerning accidents are rarely covered in the accident data. Therefore, it is often difficult to derive useful inferences for the underlying causes of accidents. This point limits the use of accident data for the purposes of determining suitable safety enhanced measures.
- Another drawback of this approach concerns the quality of accident data. Accident data itself is incomplete suffering from under-reporting. Not all road accidents are reported. Furthermore, the level of reporting varies with e.g. road user types involved, and severity of injuries. It is illustrated that the more serious the injury, the more likely it is to be registered with the police, according to estimations in the Netherland [35]. In light of reports [36,37], there are several times more cycling injuries than reported by the police in many countries. This is partially because cycling injuries only from crashes with motor vehicles are likely to be included in the police data.
- Although the number of deaths caused by road accidents is high, accidents are still rare events when accident frequencies are segregated by location, time and type.
- Before hazardous sites and situations are identified or safety-enhancing measures are evaluated, a large number of serious accidents are expected to take place first, and therefore a long period of accident recording is required. This raises concern about ethical problems.

To overcome these drawbacks, other methods have been suggested in traffic safety research. In-depth accident analysis is one of them, where detailed information about accidents is collected. Another method is the Traffic Conflict Techniques (TCT), which concerns non-accident data, i.e. traffic conflicts. Naturalistic Driving Observation (NDO) is a recently developed method that can integrate human behavioral, vehicular and environmental situations before, after and during accidents or critical events. These three methods are introduced in the following sections.

2.2. In-depth accident analysis

The National Transportation Safety in USA initiated the concept of in-depth accident study. In such an investigation, extensive data in a wide range of fields before, after and at the moment of crashes can be collected and analyzed. Over the years, this approach has been recognized to be essential for improving traffic safety, and respective investigation teams were built in several countries.

In Germany, in-depth data collection was first used in 1973. The collected data included information on failure and behavior patterns in accidents. Data was collected by questioning persons involved in accidents at site. Medical University of Hanover, supported by the Federal Road Research Institute, organized this work. Based on this work, a joint project German In-Depth investigation Accident Study (GIDAS) was established in 1999, financed by the German Government and automobile industries. GIDAS is the largest investigation project in Germany and presumably the leading representative road traffic accident investigation in Europe [38].

The geographical investigation regions of GIDAS cover Hannover and Dresden areas. In the two cities, approximately 2000 traffic accidents are annually selected and documented [39]. In investigations, a specialist team, consisting of a technical team and a medical team, goes directly to the accident site immediately after the accident occurs. In addition to investigations at site, surveys and hospital examinations are further administered. In this way, the team can collect large amounts of information concerning accidents, such as environmental conditions, road design, traffic control, accident consequences (e.g. degrees of deformation, impact contact points for passengers or pedestrians) and so on [40]. These data allow the reconstruction of accidents and documentation of injuries. Various stakeholders benefit from the collected data to improve road traffic safety within their respective fields. For instance, legislator can recognize negative effects of current traffic laws and identify future legislation areas by studying accident cases in detail; road design can be more protective in accordance with feedbacks regarding road traffic engineering; contributions of in-vehicle active safety systems to accident avoidance can be evaluated by including variables associated with active safety techniques[38].

In Sweden, there is also a policy to conduct in-depth investigations, which are carried on in three levels in terms of scopes of involved accidents and executive departments [41]. The Swedish Accident Investigation performs in-depth studies of the first level. They cover fatal accidents with more than five victims or with principal system problems with two to three road traffic accidents being investigated each year. In the second level, fatal accidents that are selected by the Swedish National Road Administration together with Regional Road Administration (RRA) are studied, and about 50 studies are conducted each year. In-depth studies of all fatal accident are performed in the third level by RRA offices, involving about 450 accidents each year. The United Kingdom (UK) has a long tradition of in-depth accident investigations. The Co-operative Crash Injury Study (CCIS) and the One-The-Spot (OTS) are two layers in the multi-layer accident collection system in the UK. The Project CCIS, funded by Department for Transport and automotive industries, has investigated motor vehicle accidents since its inception in 1983 with aim to provide an insight into how people injured in road traffic accidents [42]. The project OTS was commissioned by the Department for Transport and the Highways Agency and was aimed to collect high-quality crash data for better understanding accident causation concerning various factors and injury mechanisms by investing 1,500 road traffic accidents covering all road user types [43].

In other EU countries, such as France, Finland, Holland and Denmark, and in the USA, there are also in-depth accident investigation or study centers [40,41,44]. In-depth accident investigations are implemented around the world with various focuses. These work indicates that this approach has the capability to collect detailed and comprehensive accident information, making it possible to uncover accident causations, reconstruct accident proceeding and study the consequences of accidents. However, it is very expensive to obtain such abundant data that can generate representative conclusions regarding safety. Each in-depth accident study requires financial support from public or private sponsors.

2.3. Traffic Conflict Techniques (TCT)

Due to the limitations of road accident analysis, traffic conflicts have been advocated as non-accident data to analyze road traffic safety. Perkins and Harris originally developed a formal procedure in 1967 for observing traffic conflicts in order to research safety problems related to motor vehicle construction [45].

The approach used in this research was called Traffic Conflict Techniques (TCT). The technique TCT concerns observing, recording and evaluating the frequency and severity of traffic conflicts at specific locations by a team of trained observers.

In the first traffic conflict study by Perkins and Harris, a conflict was defined as any potential accident situation resulting in evasive actions, such as braking and swerving that were identified by appearances of brake lights and sudden lane changes. The simple definition has since been refined to incorporate categories of road users and measures of time and space between road users [46].The internally accepted definition of a traffic conflict was established in the first International Traffic Conflicts Workshop in 1977 [47]:

"*A conflict is an observable situation where two or more road users approach each other in time and space to such an extent that a collision is imminent if their movements remain unchanged.* "

The use of traffic conflicts to evaluate traffic safety is based on the hypothesis that there is a close relationship between conflicts and accidents. On the one hand, it is assumed that there is a causal relationship between conflicts and accidents. Since most accidents involve evasive actions, it is believed that similar processes are involved for accidents and conflicts, especially serious conflicts, and therefore accidents and conflicts represent measures of the same process. In other words, conflicts and accidents should share similar temporal and spatial characteristics. Zimolong illustrated the sequences of events resulting in accidents and conflicts as shown in Figure 2-1, indicating that a conflict resulted from the same type of evasive actions as an accident does [48].

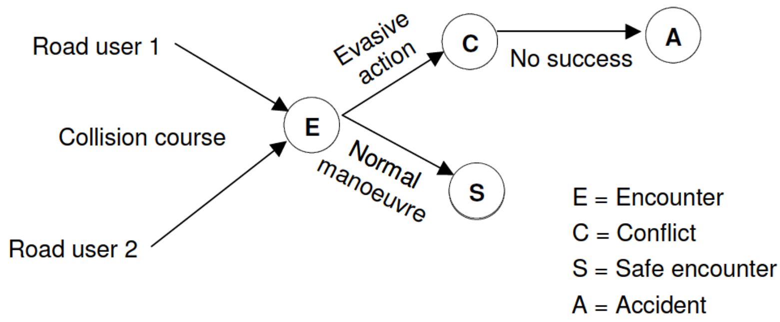


Figure 2-1 Sequence of events resulting in conflicts and accidents [48]

On the other hand, there is an assumption of a statistical relationship between conflict and accident occurrence. It is believed that the more frequently conflicts occur, the larger the number of accidents must be. Traffic conflicts occur considerably more frequently than traffic accidents. For this reason, a significantly shorter study period is needed to establish statistically reliable results, which is the most appealing aspect of the use of conflict data compared to accident data. Furthermore, traffic conflict analysis also implies a "*proactive*" approach in contrast with accident data analysis as "*reactive*", eliminating the ethical problem associated with the need of many injuries and fatalities before safety problems are resolved [49]. With regard to the relationship between accidents and conflicts in terms of occurrence frequency, Hydén employed a pyramid as shown in Figure 2-2, and indicated that there would be continuous increase in the number of events with the decreasing severity levels. This was based on the principle that the interaction between road-users can be described as a continuum of safety-related events with varying severity levels [50]. In this pyramid, accidents are found at the very top and the safe events at the bottom. The majority of events are undisturbed passages, in which road users pass independently of each other. A small portion of events results in conflicts. In conflicts, road users approach each other on a collision course and some degrees of evasive actions are required. Conflict events range from potential, slight and serious with the increasing severities of evasive actions. A smaller portion of events is accidents resulted from situations where evasive actions start too late, or there is no time for evasive actions at all. Accidents include injury accidents and fatal accidents.

Since the first application of TCT in 1967, this method has generated immediate interest and spread in many countries, e.g. France, Britain, Germany, Holland and Sweden. Different TCTs have been developed in countries where the researchers consider TCT as a possible complement to the traditional accident data analysis for safety evaluation. A literature review in 1983 listed as many as two hundred related studies [51]. However, researches soon revealed some weaknesses of this approach and some researchers were skeptical of this approach. This has limited its practical use and hindered its general development and acceptability [25,52]. Its problems primarily concern the validity of TCT and the reliability of conflict measurement.

The validity of TCT mainly focuses on the level of statistical correlation between observed conflicts and accident data. The need for validation stems from the long-standing tradition of using accident data for safety measure [25]. According to TCT studies in the early years, a part of studies suggested the existence of acceptable level of correlation, while another part indicated poor correlation level [52]. While the debate prevails, studies using US TCT and Swedish TCT have shown that observed conflicts could successfully predict the number of accidents in an acceptable level, indicating that traffic conflicts are good surrogates of accidents [53,54].

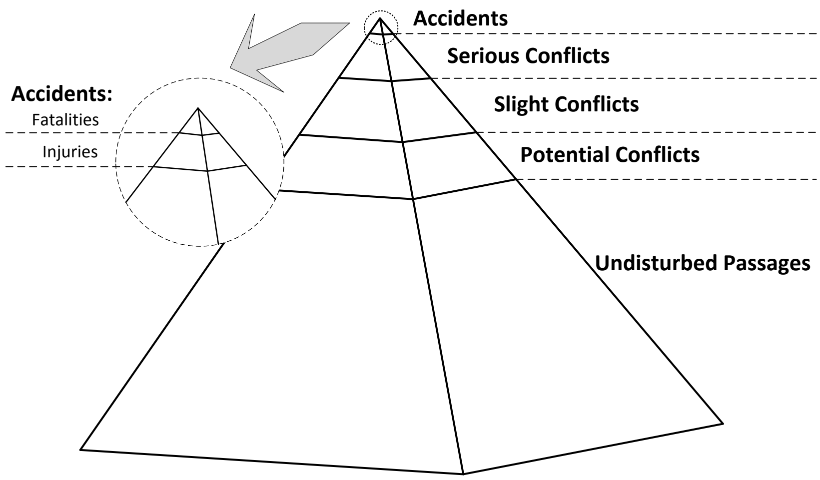


Figure 2-2 Safety pyramid consisting of a continuum of events with varying severity levels [50]

Criticism concerning reliability issues is related to subjective judgment of speed and distance by trained observers [55]. There are generally two aspects of unreliability in subjective judgment: "*intra-rater variation*" and "*inter-rater variation*" [25]. "*Intra-rater variation*" arises out of the inconsistencies of an individual observer for reasons of e.g. lack of training, fatigue, excessive numbers of conflicts, poor definition of conflicts and complexity of conflict types [56]. To remedy this problem, video recording can be used to verify the observation results [57]. "*Inter-rater variation*" is related to variability in interpretation of a given situation between different observers, particularly between observers of different countries or teams. The first international comparative study incorporating four teams of observers [58,59] and a full-scale conflict study involving traffic safety teams in twelve countries [60] revealed differences in frequencies of conflicts observed by different teams. The studies suggested that the differences were probably caused by that conflicts were differently defined and observed. It is also argued that variations in subjective observation may still exist, even if conflicts are well defined and observers are well trained [25].

In TCT application, different safety indicators have been developed to evaluate safety severities. In subjective observations, Time-to-Accident (TA) is used to distinguish serious conflicts from slight conflicts. TA means the time remaining from when evasive action is taken until the collision would have taken place if involved road users had not changed speed and direction. TA values are calculated based on speed and distance estimated by trained conflict observers. For the purpose of determining severity, TA values must be used in conjunction with estimated speed [50].

Given that the subjective measure is a frequent subject of criticism in TCT method as described above, alternative indicators of more objective measures were proposed, such as Time-To-Collision (TTC) and Post-Encroachment-Time (PET). TTC was originally suggested by Hayward who described TTC as "*the time that remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained*" [61]. In calculating TTC values, the evasive action is not considered. Instead, once a conflict course is determined, a series of TTC values will be obtained during this conflict course. The minimum TTC value is regarded as the final TTC value of a collision course. In practical studies, a threshold of TTC value is preset to determine the severity level of conflicts, and the factor of speed is not taken into account. PET is one variation of TTC and is used to measure a process in which two road users do not involve in a collision course, but pass over a point with a slight temporal difference [62]. Compared to TTC, PET values are easier to obtain, as no speed and distance data is required. However, the PET concept is only applicable to critical events involving road users in transversal or crossing trajectories. Many other derivatives of TTC and PET have been proposed in recent studies with specific research purposes, such as, Time-Exposed-TTC and Time-Integrate-TTC [63], Time-to-Zebra [64], and Gap-Time, Encroachment-Time and Initially-Attempted-PET [65]. Which safety indicator to use depends on what the research aims are and to what extent resources are available for a research. The objective measures largely rely on video data analysis rather than on-site observation. The use of video-analysis allows repeated observation of difficult and complex conflict situations, and guarantees precise measures of speed and distance as well. With the fast development of information technologies, processing of video data is being less time-consuming and less laborious. The introduction of video recording analysis is a huge progress of TCT, conforming to the TCT development needs exactly as suggested by Chin and Queck [25].

2.4. Naturalistic Driving Observation (NDO)

The TCT method is applicable for variant research purposes. It is mainly used to assess safety changes caused by safety enhancement measures in device, layout, design and procedure through before-and-after study [66]. It can also be used to study interactions of specific road user types. However, in most studies, conflicts were collected at a specific location, whether by on-site observation or by video recording analysis. The observation restrained in limited locations make the results sensitive to site-specific factors related to roadway design, average speeds and traffic flows, especially when specific conflict types or conflicts between specific road user types are aimed to be collected [21]. This limitation raises the need to collect conflicts in a dynamic process where the environment is changing. This would largely extend the application of traffic conflicts in safety research. Naturalistic Driving Observation (NDO) is such a method to meet this need [67]. It can collect and evaluate conflicts as well as interactions of road users in a spatially changing process.

2.4.1. NDO and its advantages

Naturalistic Driving Observation (NDO) is a relatively new approach within traffic research. It can be defined as "*a study undertaken to provide insight into driver behavior during every day trips by recording details of the driver, the vehicle and the surroundings through unobtrusive data gathering equipment and without experimental control*" [68]. In a typical NDO study, passenger cars, generally the subjects´ own cars, are equipped with cameras and various sensors. The subjects can decide where and when to drive, and drive the equipped cars in their usual way without specific instructions and interventions. For a long period of time ranging from several weeks to several years, the installed data acquiring devices record vehicle movements (such as driving speed, acceleration/ deceleration, direction and geographical positions), driver behaviors (such as eye, head and hand maneuvers) and environmental conditions (such as traffic densities, time headway, road conditions and weather characteristics). The collected data allows the observation and analysis of interrelationship between driver, vehicle and environment (including road, traffic conditions and weather) in normal driving conditions, conflicts and even crashes.

The NDO conduction procedure might slightly vary in different studies. There is no standard guideline to follow. However, an Implementation Plan that was modified from the Implementation Plan for Field Operational Test (FOT) can be used as a reference [69]. This NDO Implementation Plan includes all steps that have to be considered in conducting NDO studies, such as planning, preparing, executing, analyzing and reporting a NDO study, and gives information relevant for legal and ethical issues.

There are a number of traditional approaches for road safety research, such as historical accident analysis, in-depth accident investigation, driving simulators, instrumented vehicles and self-reports. Whereas these methods could greatly contribute to the understanding of road user behaviors, they concern several limitations [70,71]. The first two traditional methods have been discussed previously. A main downside of them is the lack of direct observation of accident events and the lack of sufficient information to derive causal explanation for accidents. Driving simulator is widely used and appreciated for investigating road user behaviors. It allows studying variables leading to specific behaviors, eliminating influences of external confounding variables that can be strictly controlled. However, the results from driving simulator studies are not always easily transferred to real traffic situations, as both traffic environment and the vehicle characteristics are artificial and only approximations of reality. In field experiments with instrumented vehicles, participants drive real cars in real traffic environment. However, they are often asked to perform specific behaviors, for example talk on a mobile phone or perform a "cognitive task". The consequence of performed specific task is observed for behavior measures. Moreover, such studies normally involve a researcher present in the car. The presence of observers and equipment makes participants aware of being observed and affect their driving behaviors. Therefore, field experiments with instrumented cars cannot get access to the daily "*natural*" driving behaviors. Self-report is also a widely used method to study driving behaviors by means of questionnaires with relation to driving exposure ("*how long do you drive annually?*"), risky driving behaviors ("*how often do you talk on mobile phone while driving?*") or the frequency of crashes in driving. Such a method can more easily reach a representative sample and make generalization of the results to a larger population possible. However, it concerns indirect observation and relies on the subjective reports of road users´ own behaviors. The results from self-reports are subject to various biases.

The approach method NDO can overcome these problems associated with traditional methods, as it can provide direct, objective and comprehensive observation of road users´ "*natural*" daily behaviors in both normal and critical situations. Compared to the traditional methods, NDO has larger potential to get insight into how critical situations take place and find out possibilities to make the traffic system safer.

2.4.2. Review of NDO studies

The Virginia Tech Transportation Institute (VTTI) pioneered NDO in the project 100-Car Naturalistic Driving

Study. Since then, many NDO studies have been undertaken for different research targets. A literature review of NDO studies was made in the project PROLOGUE, aiming to assess the feasibility and usefulness of a large-scale NDO study in Europe and to provide recommendations for such a large-scale study [70]. Review of NDO studies were also made in the first stages of large-scale NDO studies in Australia and in Europe [72,73]. Large-scale NDO studies have been or are being conducted in some countries, such as "*100-car NDS*" and SHRP2 in the USA, "*Australian 400-car NDS*" in Australia and "*UDRIVE*" in the EU. Large-scale studies normally involve a great number of cars (more than 100 cars), cover national or international regions and last a long period.

100-car NDO is the ground-breaking NDO study that was conducted by VTTI in the USA [74]. In this study, data was collected on 241 drivers who drove 104 fully equipped cars in Northern Virginia/Washington, DC metropolitan area for twelve to thirteen months. It generated approximately 2 million vehicle miles and forty-three thousand hours of data. This study was initiated with several research goals in mind. A primary goal was to provide a high level of detail concerning driver behaviors, vehicle dynamics, driving context and other factors associated with crashes and conflicts. From the data, an event database was built up, including 15 police-reported crashes, 67 non-reported crashes, 761 near-crashes and 8,295 incidents. A near-crash in 100-car NDO study was defined as a conflict event where "*a rapid evasive maneuver*" was conducted, such as steering, braking, acceleration or any combination. The definition was quantified by e.g. a longitudinal deceleration of at least 0.5 g. The concept of near-crashes was similar to the serious conflicts in TCT. Incidents included the slighter conflicts and "proximity conflicts" in which avoidance actions were not observed, but the absence of avoidance actions was inappropriate for the driving safety. One of the most important outcomes of this study was that distraction and inattention were found to play a role in almost 80 percent of all the observed crashes. Besides, the 100-car NDO data have been analyzed from other perspectives. For example, the light vehicle-heavy vehicle interaction events were identified from the data set in order to investigate the interactions between light vehicles and heavy vehicles; the causal factors were analyzed for rear-end crashes/conflicts [67,75].

Another large-scale NDO study SHRP2 is the follow-up project of 100-car NDO [76]. SHRP2 NDO is the largest and most comprehensive NDO study ever undertaken. The data collection started in 2012. It was completed in 2014. Two petabytes of data were produced from 3,147 drivers in six American states for three years (most for one to two years), covering 50 million vehicle miles and 1 million hours of data recording. The recorded data included vehicle speed, acceleration, braking, vehicle controls, lane position, vehicle headway, forward and rear views of vehicles, and drivers´ face and hands. The central goal of the study was to produce unique data that could be used to study the role of driver performance and behaviors in traffic safety and how they affect the risk of crashes. The current results from the data analysis were related to rear-end crashes, focusing on understanding the relationship between rear-end crash risk and driver inattention. The inattention was measured by distracting activities (e.g. answering a cell phone, monitoring the radio), glance location, and timing of Eyes off Path. A set of 46 rear-end events and 211 near-crash events was detected. For analysis control, 257 matched baseline events and 260 random baseline events were selected. The analysis of these selected events generated several findings: "*While some activity types (like Texting) significantly increased risk, a strong significant decrease in risk was found for talking/listening on cell phone compared with not engaging* *in a phone conversation* "; "*Glances that lead to crashes may not necessarily have to be long*"; "*Dangerous glances are those during which the driver gets exposed to the risk of a rapidly changing situation*"; and "*Lead-vehicle crashes can be understood as the mismatch between glance duration and the lead-vehicle closure rate*". The results provide supports for vehicle design, driving education and road and infrastructure design. The data processing is ongoing and years are needed to output more results given the vast data size.

UDRIVE is the first large-scale European NDO study [73]. Data collection was conducted in seven EU member states. It involved 290 participants. UDRIVE put its focuses on crash causation and risk, such as distraction and inattention as well as interactions between drivers and other road users. In addition, it aimed at quantifying driving style, road characteristics and traffic conditions in relation to fuel consumption and emission levels. Furthermore, this study investigated not only behaviors of car drivers but also that of truck drivers and motorcycle riders. That is, trucks and motorcycles were instrumented by data logging sensors to record daily driving or riding behaviors and surrounding environment.

In Australia, a large-scale NDO study started in 2013 [72,77]. This study planned to recruit 400 volunteers to drive their own car for 6 months. It has raised eight questions in relation to thematic areas, such as driver personal characteristics, driving behaviors, exposure to collision risk, and causal factors to crashes/safety-critical events. Data collection and analysis focused on finding out the answers to these questions and studying the relationship between these thematic areas. From the answers, countermeasures were expected for improving intersection safety, reducing crashes concerning speeding, vulnerable road users and fatigue and inattention, and improving intelligent vehicle safety technologies.

From a large-scale NDO study, several research problems can be addressed. Besides large-scale studies, many small-scale NDO studies were undertaken to concentrate on specific research issues. NDO provides information that would be difficult to obtain by other methods. The research issues that NDO as an ideal method was used to handle can be summarized as follows:

- Identification of crash contributing factors, e.g. distraction, and fatigue or drowsiness ;
- Driving behaviors of specific driver groups, e.g. novice drivers, older drivers and drivers with diseases;
- Effects of road design and weather conditions on driving behaviors;
- Interactions between car drivers and other road users;
- Effects of in-vehicle information devices or advanced driving assistance system on driving behaviors;
- And relationship between driving patterns, fuel consumption and vehicle emissions.

Distraction

Distraction has been found to be a major contribution factor to road accidents [78,79]. Distraction in driving was the primary research focus in the majority of NDO studies. The four large-scale NDO projects described above all involved research on driver distraction. NDO is a multifaceted method within the field of driving distraction. It is suitable for investigating the prevalence of distraction in accidents. Particularly in large-scale NDO studies, a lot of accident- and conflict-events might be obtained. Results from the "*100-car NDO*" indicated that secondary task distraction and eye glances from the forward roadway were involved in a vast majority of lead-vehicle crashes [80]. The distractions of truck drivers and combined data in two earlier NDO studies were investigated: in one study, vehicle kinematic, video and audio data were collected from a group of 103 truck drivers for twelve weeks [81]; in another study, the driving data of a group of 100 truck drivers were observed for four weeks [82]. The key finding from the first study was that drivers were engaged in secondary tasks in 71 percent of crashes, 46 percent of near-crashes, and 60 percent of all safety-critical events. In the second study where 41 long-haul truck drivers were observed, 2,737 serious conflicts (no crashes were recorded in this study) were detected and examined. 178 of them were attributed to driver distraction.

In addition to the research on distraction prevalence in crashes and conflicts, the recorded information before, during and after events allows for identification and description of distraction patterns and how often drivers being engaged in distraction. Such a NDO study for estimation of distraction exposure was conducted by observing 70 drivers for one week using a continuous video recording system [83]. This short-term study showed that distraction was a common component of everyday driving and the most common distraction pattern was conversing accounting for 15.3% of the observed distraction duration, followed successively by (preparing for) eating and drinking (4.61%), smoking (1.55%) and using a mobile phone (1.3%). In a similar study, twelve drivers with young children were monitored for three weeks in order to investigate child-occupant-related distractions [84]. It was found that the child-related distraction activities included looking at the rear seated children (76.4%), conversing with the children (16%), assisting the children (7%) and playing with them (1%).

Fatigue or drowsiness

Drowsiness or fatigue is also a significant contrition factor in road accidents. This factor is in particular interesting for commercial drivers, as they often drive for long time and at night. The reviewed relevant studies were all conducted in the United States. Safety-critical events associated with fatigue issues among long haul (LH) truck drivers were studied in a study of Dingus et al. [75]. In this study, sensor and video data were collected from 56 LH truck drivers, including 13 team drivers (2 drivers per team) and 30 single drivers. Fatigue was found to be a critical issue in LH truck safety. In addition, single drivers had more critical events than team drivers did; the critical events of team drivers due to "*very drowsy*" occurred mostly at night, while critical events of single drivers occurred mostly in the afternoon.

Fatigue associated with LH truck safety was also addressed in a study of Hanowski et al. [85]. The objective of this study was to investigate fatigue related to the revised Hour-of-Service (HOS)-regulation in the US. The revision of HOS-regulation included a two-hour extension of off-duty time from eight to ten hours, and a one-hour extension of maximum daily driving time from 10 to 11 hours. The fatigue was not measured directly but estimated based on the daily sleeping hours of the drivers. In order to test the effects of the revision, eighty-two LH truck drivers were observed for sixteen weeks by use of instrumented trucks and sleep monitors. No increase in occurrence of critical events was found in the eleventh hour. This finding indicated that the one-hour extension of driving time in HOS regulation had no detrimental impact on driving safety.

In another study of Hanowski et al., local/short-haul (L/SH) trucks were instrumented to observe 42 L/SH truck drivers for two weeks by a video recorder, a driver alertness measure, and driver attention and performance measures [86]. L/SH-driver-at-fault critical events were of primary interest in data reduction. The results from data analysis indicated that fatigue was present immediately prior to driver involvement in at-fault critical incidents. A further analysis of the data from this study was aimed to identify factors associated with drowsiness or fatigue [87]. By investigation of the 2,745 drowsy events, younger and less experienced drivers were found to be more frequently drowsy. In addition, a strong relation was found between drowsiness and time of day: drowsiness was more likely to occur in the early morning and within the first hour of work shift.

Driver characteristics

According to the epidemiological research, it consistently shows that novice and older drivers are at increased accident risk, more than the drivers in other ages are, likewise are drivers with chronic diseases. Some NDO studies have been undertaken to investigate behaviors and accident risk of such groups of drivers.

Regarding the group of young drivers, a study used an in-vehicle data acquisition system, consisting of cameras, vehicle position sensors and vehicle status sensors, to record behaviors of 42 newly-licensed teenagers and their parents for eighteen months [88]. One primary finding was that crashes and near-crashes among teenagers were significant higher in the first six months, and decreased in the following twelve months. Another important finding was that the number of crashes and near-crashes of teenage participants were significantly higher when compared with the number of crashes involving adults. This finding was consistent with the previous studies based on self-report data and accident data analysis. Driving behaviors of teen drivers were also studied in another study [89].This study tested a program, in which it was required to accompany a teen driver in the first three months after licensure. Sixty-two novice drivers and their parents voluntarily participated in this study. Vehicle speed, acceleration and derivers´ behaviors were recorded and used to measure risk-taking indices. The results showed that the risk-taking behavior of the teen drivers was related to various factors, such as gender, sensation-seeking tendency, driving behaviors of their parents and supervision amount. The relation between risk-taking behavior and drivers´ low driving experience during accompanied driving period highlighted the importance of the tested program. A study of McGehee et al. also focused on driving behaviors of novice young drivers by monitoring a group of twenty-six novice young drivers using event-trigger video recording system [90]. Two different behavior patterns were observed in these young drivers: drivers of one pattern rarely involved in safety-critical events, and drivers of another pattern often involved in critical events.

Behaviors of the older driver group were studied by use of NDO in two reviewed studies. The two studies focused on the driving exposure and driving patterns. The first study recorded driving trip information of 61 older drivers for one week, including time of day, driving areas and night driving [91]. Significant discrepancy was found regarding driving exposure and patterns between self-report of daily diaries and the recording data by NDO, indicating that a significant number of trips were missed in the diaries. This result highlighted disadvantages of the self-report as a method to study driving behaviors of older drivers and the benefits of combining NDO and self-report in this field. The second NDO study was conducted to investigate the driving patterns of older drivers in winter. Forty-seven older adult drivers were observed for two weeks, to record when, where and under what weather conditions they drive [92]. Older drivers´ travel exposure and patterns were found to be associated with many factors, such as weather, road conditions and self-rating of driving comfort.

In-vehicle driving support system test

Naturalistic driving data allow for investigation of driving behaviors associated with in-vehicle systems in question, to understand how drivers compensate and adapt to the systems. The standard method for in-vehicle system test is Field Operational Test (FOT). A FOT is defined as "*a study undertaken to evaluate a function, or functions, under normal operating conditions in road traffic environments typically encountered by the participants using study design so as to identify real world effects and benefits*" [103]. FOT is a different method from NDO. However, NDO use the same observation equipment, techniques and even conditions as "naturalistic FOT", in which unobtrusive observation is conducted when participants drive their own cars in real traffic context following their daily traffic routine. In this case, it is hard to distinguish the two methods, and therefore naturalistic driving data collected by either NDO or FOT can be used for the same research purposes [69]. With regard to test of in-vehicle support system, a lot of interesting questions could be addressed, for example, how and when driver use the system to be tested, whether it generates any side effects, and whether it changes and affects drivers´ behaviors. A NDO study was carried out to verify the unintended side effects on drivers´ behaviors of Forward Collision Warning (FCW) and Adaptive Cruise Control (ACC), with the hypothesis that there would be an increase in secondary activities due to the presence of the two assistance systems [93]. The result did not support the hypothesis. In another NDO study, naturalistic driving data was collected, from which avoidance response time points in crashes and near-crashes were abstracted in order to evaluate and develop the performance of Collision Avoidance Systems (CAS) [94].

Interaction between different road user types

Two studies were reviewed to focus on the interactions between light vehicles (i.e. passenger cars) and heavy vehicles. The two studies investigated the interactions between light vehicles and heavy vehicles from the perspective of the light vehicle drivers [74] and the heavy vehicle drivers [95], respectively. The first study analyzed the data set in "*100-car NDO*". The second study instrumented heavy vehicles with the same data collection device set as in the "*100-car NDO*" and observed the drivers for one to two weeks. In the two studies, safety-critical events between light vehicles and heavy vehicles were identified and analyzed. The results from both studies indicated that light vehicle drivers were responsible for the majority of detected events. Moreover, the most frequent contributing factors to critical situations by light vehicle drivers were difficulties of decelerating and stopping, whereas by heavy vehicle drivers´ contributions factors were difficulties when changing and crossing lanes. The studies implied the possibilities to study interactions between different types of road users by use of NDO. However, challenges exist in interpretation of behaviors of road users in the vehicles that are not instrumented.

Other NDO studies

Besides the research issues discussed above, other issues could also be studied by use of NDO. NDO studies have been carried out to investigate the behaviors and driving capabilities of drivers with various disease and health conditions, such as dementia [96,97] and visual impairments[98]. In standard NDO studies, recoded environmental information by cameras and GPS logger offers potentials for studies concerning relationship between environment factor and traffic safety. Although no NDO studies are reviewed especially for this purpose, environmental conditions were, for instance, combined to analyze the contributing factors to drivers´ inattention in "*100-car NDO*" [75]. In addition to the study issues relevant for traffic safety, environment-friendly driving, i.e. eco-driving, was also considered in NDO studies. In studies within this field, driving styles were investigated associated with fuel consumption and green-house emission [99-101].

2.4.3. Review of Naturalistic Cycling (NC) studies

Naturalistic data could be collected not only from equipped motorized vehicles (such as cars, trucks and buses), but also from instrumented bicycles. While cycling safety is receiving more attention in the area of traffic safety, a number of naturalistic cycling (NC) or quasi-naturalistic cycling studies have been conducted to understand cycling dynamics, bicyclist behaviors and cyclists´ interactions with other road users.

The naturalistic driving method was first adapted to investigate riding experience and behaviors of bicyclists in Australia [102]. In this study, helmet-mounted cameras were used to observe six commuter bicyclists. From 46 hours of video footage, 36 near-collision events were identified. Although no contribution was made for suggestions to improve cycling safety due to the limited sampling data, this work proved the feasibility of collection and analysis of naturalistic cycling data. Another naturalistic study of commuter cyclists was conducted in Greater Stockholm, Sweden [103]. Besides video cameras, GPS logging devices were used to collect GPS-coordinate data. Sixteen commuter cyclists were observed in their daily cycling, generating 240 hours of cycling data. From these data, 506 problems were identified and described in terms of safety, mobility and accessibility in cycle network. These problems were served as useful input in improvement of cycling plan in Greater Stockholm. A naturalistic cycling study was carried out by Dozza M. et al. with more complicated equipment, including cameras, inertial sensors, GPS loggers and brake force sensors [104]. The daily cycling data of twenty cyclists were recorded, offering a set of naturalistic cycling data unique in quantity and quality. By analyzing the collected 114 hours of cycling data, sixty-three critical events were identified, of which six were crashes. Comparing the selected 126 baseline events and 63 detected critical events, the statistical associations were verified between critical events occurrences and factors concerning weather, environment, location and infrastructures.

The studies aforementioned focused on the general critical situations or problems in the cycling trip. Some reviewed studies particularly concerned interactions between motorized vehicles and bicycles. The interactions were studied primarily when motorized vehicles overtake bicycles. A study used instrumented bicycles to observe overtaking events on rural roads [105]. The lateral passing distances were measured, showing that vehicles passed too closely to bicycles only in 0.5% of the detected overtaking events. Another study recruited 34 participants to implement an experimental riding in a planned urban route with different bicycle facilities [106]. Overtaking events were also detected from the recorded data. These events were used to study factors that influence motorists´ overtaking distance and bicyclists´ positions, wheel angle and speed control behaviors, such as types of motorized vehicles and road features. A more complicated set was built to instrument bicycles by Llorca C. et al., which could not only measure the lateral passing distances, but also motor vehicles´ speed while passing [107]. By analyzing the about 2,000 overtaking events, it was suggested that a combine factor of passing distance, vehicle type and vehicle speed had significant influence on cyclists´ risk perception, rather than the factor of passing distance alone.

2.4.4. Weakness of Naturalistic Driving/Cycling studies

Despite the potentials of naturalistic driving/cycling methods to address questions that other traditional approaches cannot answer, there are some problems and limitations associated with this method.

First, driving/cycling behaviors are expected to be unobtrusively observed in naturalistic observation studies. However, observation is always accompanied by some sort of intrusion [108]. Although equipment is mounted as inconspicuously as possible, there are still some clues making participants aware of being under observation, which would result in some level of behavioral modification. In addition, participants are at times required to use instrumented vehicles instead of their own, when only a few instrument sets are available due to their high cost [104]. Moreover, some studies have only access to limited resources. In this case, in order to capture an adequate amount of valid data, studies are organized at the expense of natural properties. For instance, the participants were instructed to ride on specific routes at specific time period and comply with road regulations and rules [103]. For these reasons, it is argued that any naturalistic observation study can hardly be viewed as purely naturalistic [108]. However, this promising method still could address traffic safety issues, when studies are designed as naturalistic as possible by balancing study requirements and resource limitations, and careful analysis is made to understand which elements are actually natural and which are not.

Another typical problem in most naturalistic studies is that data storage and analysis are resource demanding. Since not only numerical data but also video data might be included in naturalistic data, an enormous amount of data could be generated in a study. For instance, the 100-car NDO study resulted in six terabyte of data, while the project SHRP2 resulted in two petabytes of data. The huge database puts forward a very high demand on storage capability of the network, especially considering that several researchers could analyze these data at the same time. Video data in naturalistic studies could consist of up to several years of continuous video images. Safety-critical events are the most common interesting events in naturalistic data analysis. The critical events can be identified by kinematic triggers (by searching for deceleration or yaw rates above thresholds), interview or push buttons. In studies where critical events are of interest, merely the video fragment containing useful information about the detected events are positioned and watched. However, in naturalistic studies with respect to e.g. lane-change events and bicycle facility usage, it is necessary to review manually all video data. Manual evaluation of video data is very time-consuming, even in small-scale studies [109]. Moreover, manual reviewing procedure is based on subjective decisions, facing personal variation and low accuracy. To solve this problem, (semi-) automatic video processing is being introduced in naturalistic video data analysis. For instance, the study of Dozza M. et al. tested several algorithms to recognize objectively safety-critical events by automatically detecting sudden body motion of drivers [106]. The application of automatic video processing techniques in naturalistic video data analysis would reduce resource expenses, and extend the naturalistic study possibilities.

The naturalistic data application is limited by the fact that crashes that are of main interest in data analysis are rare events. Statistics shows that an average driver needs 62 million miles of travel for an accident occurrence [110]. Statistical analysis only using crash data is limited. In previous naturalistic studies, less severe safety-critical events were used as surrogates for crashes. Less severe safety-critical events were defined differently in terms of terminology and magnitude of evasive actions. In the 100-car NDO study, near-crashes, crash-relevant conflicts and proximity conflicts were defined to represent critical events in descending levels of severity. This definition or its modification was applied in a great number of naturalistic studies. Less severe safety-critical events happen more frequently than crashes. For example, in the 100-car NDO study, 761 near-crashes and 8,295 incidents (including crash-relevant conflicts and proximity conflicts) were identified, while only 69 crashes were identified [67]. In fact, less severe safety-critical events are the same concept as traffic conflicts in the method of Traffic Conflict Techniques (TCT). As TCT has a longer history, it has formed a solid scientific basis for conflict severity classification, which can be cited in naturalistic data analysis.

2.5. Eye-tracking

While driving is considered as an information processing task, the most critical component of the information processing model is attention [67]. In many driver behavior researches, it is important to measure driver attention. It is critical to know how well drivers execute secondary tasks, and if certain tasks or interfaces are more distracting than others [111]. Numerous studies indicate that inattention and distraction are major contributing factors for motor vehicle crashes [112]. Many definitions of driver distraction have been published. The definitions could range from "*driver distraction occurs when a driver is delayed in the recognition of information needed to safely accomplish the driving task because some event, activity, object or person within or outside the vehicle compelled or tended to induce the driver´s shifting attention away from the driving task*" to "*a shift in attention away from stimuli critical to safe driving toward stimuli that are not related to safe driving*" [113]. Most of these definitions embrace four diversions of distraction: visual, auditory, physical and cognitive distraction.

Eye movements are linked with attention, and are believed to give a good estimate of where driver´s attention is directed [111]. Therefore, the real-time driver distraction detection is often based on eye movements, with the definition that "*distraction is assumed to occur, when the driver has glanced away from the forward roadway for a certain period of time, either continuously or with consecutive glances*" [111]. Eye movements can gain access not only to visual distraction but also other diversions of distraction [114]. Eye-tracking technique is used to measure foveal vision direction either in driving simulators or in real traffic using an instrumented car. In recent years, many researchers have studied eye movements to examine drivers´ distraction caused by different stimuli. These stimuli include in-vehicle technologies [115], assigned secondary tasks [116-118], anger emotion state [119] and hands-free cell phone conversations [120]. With the advances in eye-tracking technology, eye movements were used in other applications besides studies regarding distraction. For example, eye movements were measured to investigate differences in visual scanning between experienced and inexperienced drivers [121]. Drivers´ visual scanning patterns were also assessed in specific road environment based on eye movements, such as at permissive left-turns [122] and at varied complexity of intersections [123]. As mentioned previously, eye movement data were also collected in some NDO studies with the aim to identify causes of crashes or conflicts due to distraction [80,81]. The underlying hypothesis is that where and how long the driver looks at prior to a crash or a conflict can explain whether the driver or the environment is likely to be responsible for the event.

2.5.1. Techniques for eye-tracking

Eye-tracking systems are devices that can estimate the eye gaze direction and measure human eye movements. The first eye-tracking system using eye movement camera was developed in 1968 to monitor and record drivers´ on-road visual scanning behavior [124].

Many eye-tracking techniques are intrusive, i.e. they require physical contact with users. These techniques include contact lenses, electrodes, and head mounted devices. They work based on different principles. Using contact lenses, into which a small coil is embedded, eye movements are estimated according to the voltage induced in the coil by an external electro-magnetic field [125]. By placing electrodes around eyes, it is possible to measure electrical signal changes of the muscles that correspond to the eye movements [126]. Although the two techniques provide high accuracy, they are only appropriate for scientific exploration in controlled environment but everyday use. Head mounted devices are mostly based on cameras or other optical devices. They require eyes to be very close to the optical devices. Camera-based eye-tracking methods utilize properties of human eyes, i.e. the boundary between different eye components. The limbus and the pupil are common properties used for eye-tracking. Limbus is the boundary between the sclera and the iris, while the pupil property refers to the pupil-iris boundary [127]. Since eyelids can negatively affect the limbus tracking technique, pupil tracking has better accuracy. Many camera-based eye-tracking devices apply an infrared light source in order to enhance the contrast of boundaries.

In contrary to intrusive eye-tracking techniques, non-intrusive techniques, also known as remote techniques, can measure eye movements without direct contact with users. Non-intrusive devices are mostly vision-based, i.e. they capture images of eyes using camera aimed at users´ face. They also rely on eye component boundary-tracking, similar to head-mounted camera-based eye-tracking devices. (Head-mounted or off-head) Camera-based devices are the most widely used techniques for in-vehicle studies. However, camera-based eye-tracking techniques has limitations related to accuracy, sensitivity to illumination conditions and glasses use, calibration problem and so on [128].

2.5.2. Parameters for eye movements

One of the most frequently used terms for eye movements in automotive contexts is the fixation. Fixation occurs, when the eye gaze, i.e. the line of sight of a person, is directed towards to a particular location and remains for a period of time [112]. The period of a fixation is generally between 200 ms and 2000 ms. In car driving, the majority of fixations are observed between 200 ms and 600 ms [129]. However, in some situations, for example, when a car driver is waiting at a red light with few driving tasks, a fixation can last much longer. Fixations are separated by rapid eye movements known as saccades, which are another frequent term in eye movement analysis. It is generally agreed upon that very little new information can be achieved during a saccade. The reason is the phenomenon of saccadic suppression, that is, people are unaware of the blurry moving image on the retina during the saccade [130]. Therefore, the actual paths travelled during saccades are normally irrelevant in many research applications. Instead, the fixation is of primary measure of interest, since it retains the most essential characteristics for understanding cognitive and visual processing behaviors.

In analysis of eye movements, spatial and temporal characteristics of fixations are often measured. Fixation location is a spatial parameter, providing information on which area or object is being processed. Driving is a dynamic process, in which the motorists have to monitor a series of objects, such as dashboards, rear view mirrors, roadways, traffic signals, other road users etc. Scan path is another spatial parameter, which is defined by the sequence of fixations on different areas or objects [112]. This parameter is a useful measure for fixation patterns or scan patterns for the purpose of comparison across groups or traffic conditions. Duration of fixations is one of frequently used temporal parameters of fixations. This parameter can serve as a measure for driving demand. Generally, situations that require longer fixation durations are more difficult to handle than those in which shorter fixation periods are measured [131]. The time proportion of fixations on an area or object is another temporal parameter. It can be also measured to compare visual behaviors between different road user groups or traffic conditions.

2.6. Perceived risk

Perceived risk is the subjective evaluation of the risk that people incur in a given situation [132]. Subjective perceived risk is considered to play an important role in traffic safety [133]. In the driving behavior models of Klebelsberg, it is stated that dangerous situations might emerge, if the subjective safety is higher than the objective safety [29]. Based on explanations concerning objective and subjective safety aspects, Klebelsberg drafted a model along the lines in Figure 2-3. The model shows that safety improves if an increase in objective safety is not paralleled by an increase in the subjective perceived safety; safety decreases if there is an increase in subjective safety without commensurate increases in objective safety.

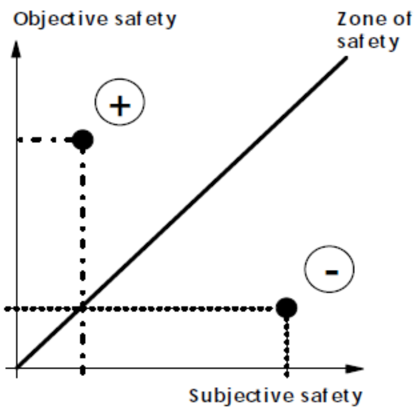


Figure 2-3 The model of objective and subjective safety

The association between subjective perceived risk and the objective safety could be explained by the relationship between risk perception and behaviors. People are likely to behave more cautiously, when they perceive themselves as vulnerable to risk [134]. In the context of road traffic, road users often engage in protective behaviors, when they perceive a high risk [135]. In contrast, risk-taking behavior is significantly related to lower risk perception, which has been indicated in many researches (e.g. [136-138]). Although a great number of researches support the relationship between risk perception and behaviors, some controversy about this relationship exists. For example, no significant correlation is found between risk perception and risky behavior among a sample of young drivers [139]; Horvath and Zuckerman indicate that risk perception is a consequence rather than a cause of risky behavior [140]. It is noted that the relationship between risk perception and behaviors is not as simplistic as described above. According to Fuller´s driving behavior model, the way how road users respond to a traffic situation depends on not only the risk perception, but also many other factors such as expectation, motivation and utilities [141]. Therefore, although risk perception is considered as a precursor of human behavior, and the understanding of risk perception is believed to be able to predict behavior [135], the relationship between risk perception and behaviors should be carefully used to explain the association between risk perception and safety.

Researches to identify the predictors of perceived risk among car drivers are prolific [175-181]. Particular attention has been paid to comparison of perceived risk between young and older drivers, between male and female drivers and between drivers in different countries or cultures, with researches investigating the relationship between driving behaviors and risk perception. Perceived risk includes two aspects: the likelihood of the occurrence of an accident and the consequence associated with the accident [142]. In these researches, a single aspect or both aspects of perceived risk were assessed. The subjects could be asked to evaluate the risk involved in a given situation for both aspects, to evaluate the probability of injury due to a given accident (for the consequence aspect or to evaluate the probability to involve in an accident in a given situation for the likelihood aspect.

While a great number of researches have focused on perceived risk among car drivers, there are only a few studies concerning perceived risk among cyclists [143-145]. These studies have focused on perceived risk of cycling itself or cyclists´ interactions with the environment. Risk perception in interactions between car drivers and cyclists has been reviewed only in the study of Chaurand and Delhomme [132]. In this study, participants were asked to measure the risk in six risky situations. Although four of the six risky situations in this study concern signalized intersections, they are not representative of car-bicycle accident scenarios at signalized intersections.

2.7. Accident Prediction Models (APM) and their application in studies of bicycle crash risk

An Accident Prediction Model (APM) usually denotes a multivariable formula to describe the statistical relationship between the safety level of roads and road factors that are believed to be related to this level. APMs are usually used to "predict" expected accident frequencies by fitting the model to the historical accident history on the investigated roads; APMs are also frequently used to identify e.g. geometric, environmental and operational factors that have a significant effect on occurrences of accidents.

As one of effective methods for road safety management, different forms of models have been developed to estimate road safety performance, including Poisson regression models, negative binomial models, multiple logistic regression, multiple linear regression, random effects models, etc. [146]. The use of statistical techniques to the analysis of accident data originated from the use of the Poisson probability model.

Poisson regression models are suitable to describe the occurrence of accidents due to the non-negative, discrete and random features of accidents, and they are usually the first choice in modeling traffic accidents. However, Poisson models have one constraint that the mean must equal to the variance. In effect, a great number of literature suggests that most accident data are likely to be overdispersed, i.e. the variance is much greater than the mean [147]. If the mean is not approximately equal to the variance, the variances of the estimated Poisson model coefficients tend to be underestimated and the coefficients themselves will be biased [148]. To solve the problem of overdispersion, negative binomial regression models have been derived from Poisson models by introducing an overdispersion parameter into the relation of mean and the variance [148]. Negative binomial regression models are well suited to describe non-negative, discrete and random features of accidents, and relax the condition of mean equal to variance of Poisson regression models.

APMs can be used for different road locations, such as road segments, intersections and routes within specific areas. Road intersections are especially focused, since intersections are a common place for accidents due to existence of several conflicting movements as well as different design characteristics. In studies by APMs, the estimated accidents could involve separately motor vehicles, cyclists, pedestrians, any combination of them or the entire population. Given the popularity of cycling and the vulnerability of cyclists, cyclist injury occurrences have been focused on with more attention in application of AMPs. Accident severity, i.e. fatal, injury, and property damage only, is also a factor in accident selection in assessing the safety level by use of APMs.

The installation of bicycle facilities is a primary intersection treatment to promote cycling. However, their effects on the cycling safety are far from clear. Previous studies have reported wide disparities in safety effects of the bicycle facilities, especially bicycle paths. Two earlier studies in Sweden indicated that the changes in accident levels that had been caused by the cycle path introduction ranged from a reduction of 44% to an increase of 82% [149,150]. There have been also much discussion and debate about the safety effects of bicycle facilities [30,151,152]. Some studies separated their safety effects at intersections and between intersections. A study in Denmark found that the implementation of bicycle lanes worsened the safety both at intersections and along links, and the implementation of bicycle path could increase injuries at intersections, while injuries could be reduced along links. The author identified that bicycle paths that end at the stop line for motorized vehicles were risky for cycling [153]. A literature review, that primarily examined the studies in European countries, concluded that bicycle paths reduced collisions and injuries at intersections with the premise of special intersection modifications [154].

Given the importance and popularity of cycling, cyclist crashes at intersections become a topic that has started to receive more attention. Several studies have modeled the bicycle crash risk at signalized intersections by APMs, aiming to find out the contributory intersection factors to bicycle crashes. For example, negative binomial models were fitted to cyclist injury occurrence data based on a large sample of signalized intersections in Canada [155]. Two-equation Bayesian models was used to study cyclist injury occurrence also using an extensive inventory of a large sample of signalized intersections in Canada [156]. Negative binomial regression models were demonstrated using motor vehicle-bicycle accident data from 115 sample signalized intersections in Japan [157]. In these studies, the considered intersection factors included traffic flows of motor vehicle and bicycles, traffic control (e.g. signal control phases), geometric design (e.g. number of intersection approaches) and built environment (e.g. presence of bus stop, presence of pedestrian overbridge). Few of them considered the safety effects of bicycle facilities. The bicycle facilities were investigated in the model in the study of [156]. However, no significant safety effects were found because very few bicycle facilities were installed at the sample intersections.

3. Car-bicycle accident analysis

It is suggested by Leon G.G. that "*for research in accident prevention, one must know the world of accidents and the appropriate world of research methodology*" [158]. Although a great number of researchers have analyzed databases of car-bicycle accidents, few of them specifically focused on accidents at signalized intersections. This chapter brings insight into the characteristics of car-bicycle accidents at signalized intersections. Accident scenarios, as a widely used accident category for accident analysis, are first defined. Car-bicycle accidents at signalized intersections are analyzed concerning the scenario frequencies based on two databases. One database is police-reported accidents in Berlin that is a typical bicycle-city. The other database is German In-Depth Accident Study (GIDAS) data, which is regarded as being representative for German [159]. Based on the Berlin police-reported database, accident causes, consequences and time are also analyzed.

3.1. Cycling in Berlin

Since the studies in this thesis are primarily carried out based on the context in Berlin, the cycling environment in Berlin is provided in this section. Berlin, the capital of Germany, has a population of 3 million. On an average working day, 88.4% of the resident population take part in road traffic in forms of private motorized transport, public transport, bicycle traffic or pedestrian traffic [160]. Among them, cycling is becoming more attractive. In the last years, the share of cycling in the routes traveled in the city has been increased by up to 50%. Around 1.5 million journeys were undertaken by bicycle daily on working days in 2008. Cycling´s share of the overall number of local journeys undertaken by the inhabitants of Berlin was 13%. This figure is more than the average bicycle modal share of 10% in Germany. Figure 3-1 shows the share of journeys by bicycles in twelve districts in Berlin in 2008.

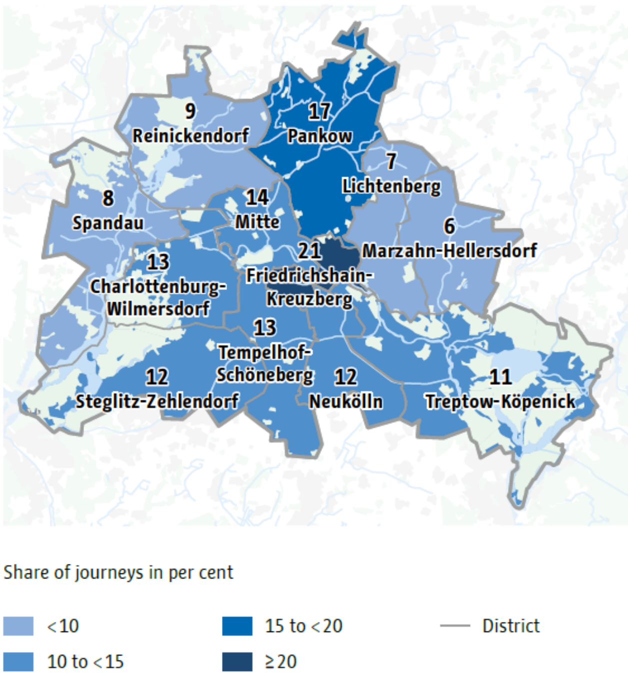


Figure 3-1 Share of journeys of bicycle traffic by district in 2008 [160]

The high cycling modal share is attributed to the bicycle-friendly politics. 1,400 km of bicycle facilities have been constructed in Berlin, including bicycle paths, bicycle lanes, advised bicycle lane and shared bus lanes. Moreover, 590 km of bicycle route have been built up through parks, woods and alongside waterways in a radial shape, covering the whole area of Berlin. These bicycle facilities and bicycle routes form an attractive cycling network, increasing the cycling activity. This network is being extended under the guidance of cycling strategy that sets the goal to achieve 18% - 20% of cycling modal share by 2025 [161]. In the cycling strategy, many other measures are contained for supporting cycling, for example, by making bicycle parking spaces more easily accessible and linking cycling to the public transport. In addition, efforts have been made to improve cycling safety, which plays an important role in people´s decision to choose cycling as the transport mode. For example, a number of modifications in road design have been implemented at intersections, such as the installation of bicycle-specific traffic signals and staggered stop lines; a series of campaigns are planned to establish cycling safety in people´s mind.

Despite these measures, the goal with regard to cycling safety is far from having been achieved. Averaged over the years 2003 to 2013, 6,797 bicycle accidents were annually registered and 12 bicyclists were killed in road accidents per year[162]. 22% among these accidents occurred at signalized intersections [18,162].

3.2. General car-bicycle scenarios defined based on geometrical configuration

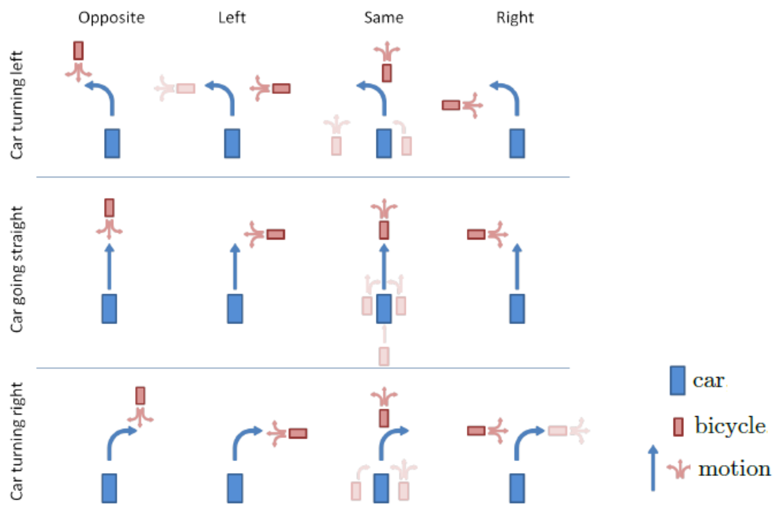
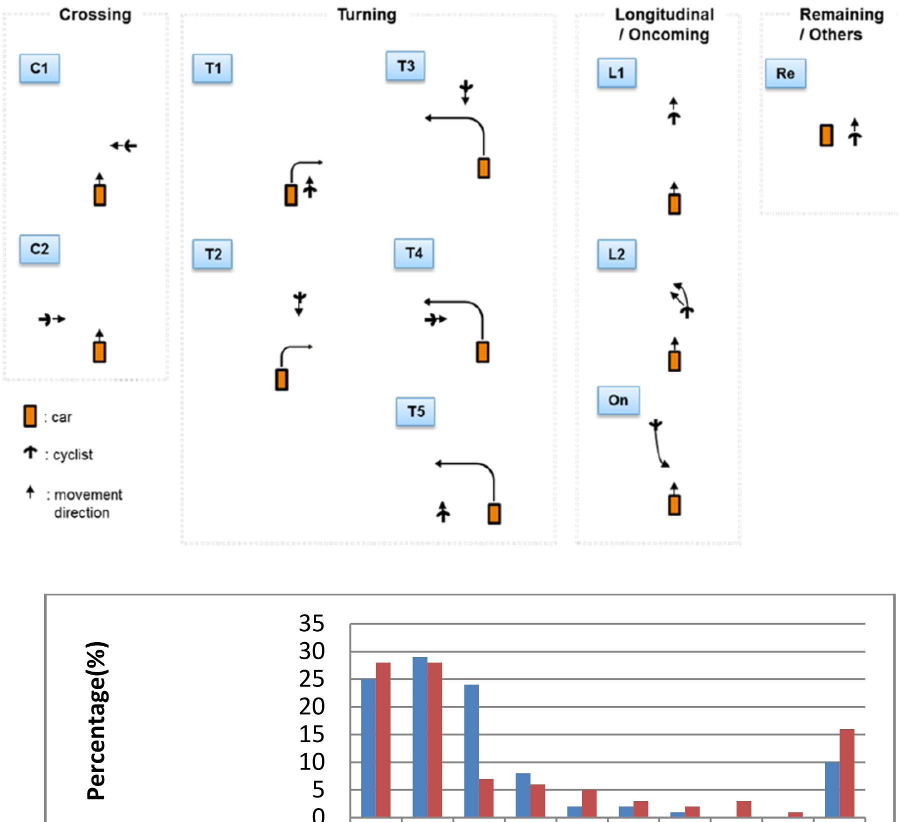


Figure 3-2 Matrix of car-bicycle accident scenarios [163]

The accident scenario is a widely used accident category to analyze accidents. While a combination of several variables, such as principal crash configuration (e.g. road user types and geometrical configuration), pre-crash dynamic parameters, road layout and basic surrounding conditions (e.g. lighting and weather), can be used to represent typical accident scenarios, a single variable can be also considered to describe accident scenarios. Geometrical configuration is one of such variables. Regarding accidents between cars and bicycles, the geometrical configuration contains the following information: the motion of car, the motion of bicycle and their relative location in the phase of pre-crash. A car or a bicycle could travel straight, turn right and turn left; in the view of a car, a bicycle can be considered to be going in the same direction, in the opposite direction, from the right or from the left. The matrix, as shown in Figure 3-2, contains all possible car-bicycle accident scenarios based on the geometrical configuration [163].



	C1	C2	L	On	T3	T5	T4	T1	T2	Re
Fatalities(%)	25	29	24	8	2	2	1	0	0	10
Seriously injured (%)	28	28	7	6	5	3	2	3	1	16

Figure 3-3 Diagrams of the scenarios (above); Distribution of accidents corresponding to scenarios, averaged over five countries (below) [164]

Several accident analysis studies have been reviewed, in which car-bicycle scenarios were defined by the geometrical configuration. A study has analyzed car-bicycle accidents with fatalities and seriously injured in five European countries based on this kind of scenario definition [164]. Ten common scenarios were distinguished and identified. The percentages of accidents corresponding to each scenario slightly deviated between countries in numbers of both fatalities and seriously injured. The average percentages of accidents for each scenario are presented in Figure 3-3. The first five scenarios, namely C1, C2, L On and T3, were dominant. They covered 88% of all the fatal car-bicycle accidents and 74% of all serious car-bicycle accidents. The scenarios C1 and C2 correspond to situations, where the car driver goes straight and the cyclist crosses from the right, and where the car driver goes straight and the cyclist crosses from the left, respectively. The two scenarios are latitude scenarios, in which the cyclist crosses the trajectory of the car in a perpendicular direction. Accidents of C1 and C1 occurred most frequently in all involved countries. The scenarios L, On and T3 are longitude scenarios. The scenario L corresponds to the situation where the car driver goes straight and the cyclist rides straight in the same direction (L1) or turns left (L2). The scenario On corresponds to the situation where the car driver goes straight and the cyclist turns left from the opposite direction. The scenarios T3 corresponds to the situation where the car turns left and the cyclist rides straight from the opposite. These three scenarios also took up a large portion of the fatalities and serious accidents.

A database documented by the German Insurance Association has also been analyzed based on scenarios defined by the geometrical configuration [165,166]. This database included 276 representative car-bicycle accidents that had been claimed to the vehicle insurance company and involved personal injuries. These accidents have been classified into four general scenarios, namely A, B, C and D. As shown in Figure 3-4, scenarios A, B, C and D represent, respectively, a collision between a (through or turning) car with a bicycle from the right (in the view of the car driver), from the left, from the opposite direction and in the same direction. Accidents of scenarios A and B were clearly more common than accidents of the others. For an in-depth analysis, the scenario A has been further subdivided into scenarios A1, A2 and A3. They correspond to collisions between a left-turning, a straight-going and a right-turning car with a bicycle from the right, as shown in lower part of the Figure 3-4. Similarly, the scenario B has been further subdivided into scenarios B1, B2 and B3. They correspond to collisions between a left-turning, a straight-going and a right-turning car with a bicycle from the left. The proportions of their corresponding accidents are also presented in this figure. Scenarios A2, A3 and B2 were most common, accounting for 42% of all the car-bicycle accidents.

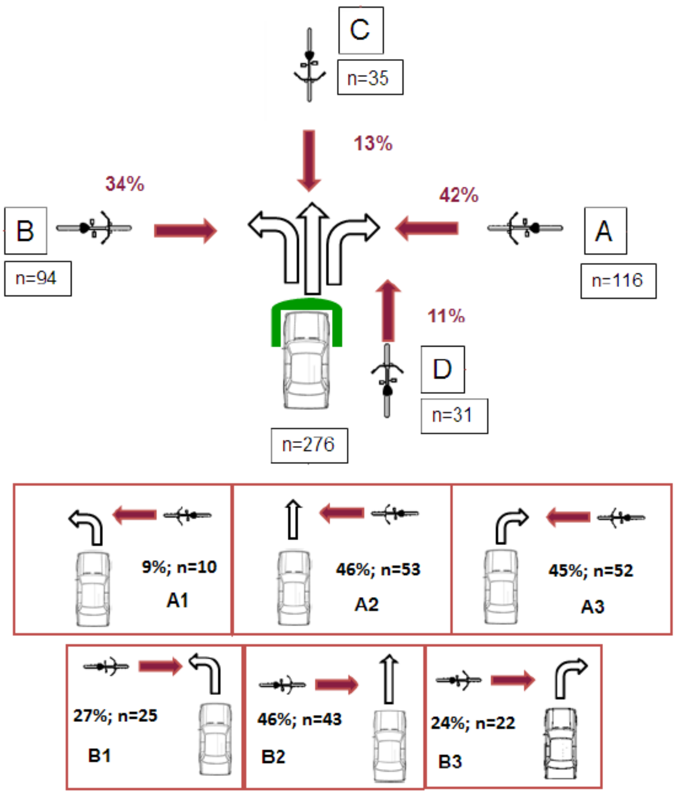


Figure 3-4 Car-bicycle accident scenarios and their distribution in number of accidents based on the accident data of the German Insurance Association [165]

3.3. Car-bicycle accident scenario definition at signalized intersections

The accident analysis in the previous section focused on car-bicycle accident scenarios in the complete road networks, including on road segments and at different kinds of intersections. Car-bicycle scenarios at signalized intersections could be different.

At a four-way signalized intersection, a cyclist could travel in 16 possible motions in the view of a car, as shown in Figure 3-5. The car and the bicycle could go straight, turn right and turn left. These motions could produce more accident scenarios than those presented in Figure 3-2. One of the reasons is that the trajectories of bicycles are more flexible than that of cars. Travelling in the wrong direction is popular in daily riding behaviors. A study in Germany has revealed that about 10% of cyclists irregularly ride in the left side of the road [167]. In addition, the presence of two-way bicycle paths at intersections could also generate the bicycle flows "*in the wrong direction*". As a result, for example, the scenario, in which a straight-going car collides with a bicycle from the right (i.e. scenario C1 in Figure 3-3 and scenario A2 in Figure 3-4), could be subdivided into two scenarios at intersections. The first scenario would then concern a straight-travelling car with a bicycle from the right in the right direction (in motion 11 in Figure 3-5), while the second scenario would concern a straight-travelling car with a bicycle from the right in the wrong direction (in motion 13 in Figure 3-5). That is, this scenario categorization approach considers the variable of road layout in addition to the geometrical configuration.

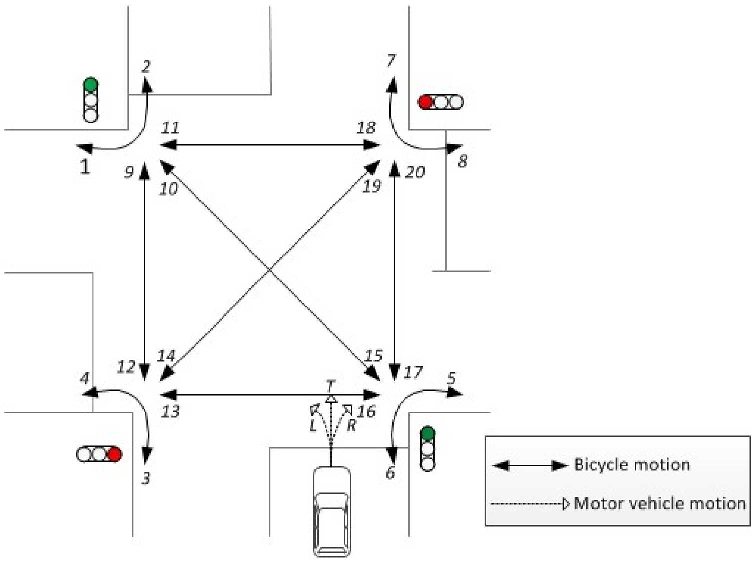


Figure 3-5 Possible motions of the bicycle in the view of a car at a four-way signalized intersection

The possible motions of bicycles are numbered as shown in Figure 3-5. They include travelling through intersections in the right direction in motions 11, 12, 16 or 20, travelling through in the wrong direction in motions 9, 13, 17 or 18, right-turning in motions 1, 3, 5 or 7, direct left-turning in motions 10, 14, 15 or 19 and indirect left-turning in the wrong direction in motions 2, 4, 6, or 8. In this thesis, the scenarios are denoted by the motion direction of the car, namely R (Right-turning), L (Left-turning) and T (Through-going), and the bicycle´s motion direction number. For instance, the accident scenario between a right-turning car and a through bicycle in the same direction is typed as R20.

Based on this kind of scenario definition, two accident databases were analyzed in the following two sections. One database was police-reported database in Berlin. The other database was the data of GIDAS.

3.4. Accident analysis based on police-reported database in Berlin

The applied police database covered the registered car-bicycle accidents at signalized intersections in Berlin from 2003 to 2013. In this database, there were 13,036 car-bicycle accidents. These accidents were documented by a set of variables, such as accident geographical locations, accident date and time, road user types, accident causes, and accident consequences (only in accident data in 2013).

In this section, accidents in this database were classified into corresponding accident scenario according to the accident variable of symbols. Using the common symbols as examples, how accidents with different symbols were categorized into corresponding scenarios was introduced. The analysis reveals all possible car-bicycle accident scenarios and their frequencies. Based on this database, accidents were analyzed also concerning causes, consequences and time. The analysis results show the common causes of car drivers and bicyclists, the injury severity and accident distributions over months.

3.4.1. Accident scenarios

Two variables might be used to categorize accidents into scenarios as defined in section 3.3. One was "*the type of accident*" (Unfalltyp in Germany). This variable "*describes the conflict situation which resulted in the accident, i.e. a phase in the traffic situation where the further course of events could no longer be controlled because of improper action or some other causes*" and "*indicates how the conflict was touched off before this possible collision*" [13]. An accident type is normally labeled with three-digit codes. However, only single-digit codes have been used for the variable of "*type of accident*" in the police database. It is insufficient for accident scenario categorization.

Another variable, which might be used to categorize accidents into scenarios, is the symbol system. Berlin police authority has developed the symbol system. It contains 205 symbols. Every accident is assigned a symbol in the accident document. A symbol consists of arrows, which represent road users. The arrow direction states the movement direction, the starting segment of an arrow states where the road user comes from and the arrow marked with a cross line represents the road user who is responsible for the accident. The symbols as well as their numbers and the meanings of their components are presented in Appendix 3.2. A symbol does not correspond to a fixed scenario. To which scenarios a symbol corresponds also depends on other variables, including the road user types that each arrow represents, accident causes, accident geographical location that are decided by the geographic coordinates and the symbol rotation angle in the geographical map. Together with these variables, the symbol system was used to categorize accidents of the police database in this work.

This section uses the common symbols as examples to introduce how accidents with different symbols were categorized into the corresponding scenarios. Figure 3-6 shows the common symbols in the applied database.

The most frequent symbol in the database was Symbol 56. This symbol involves a right-turning road user and a through moving one. The right-turning one is marked with a line in the symbol, representing the at-fault road user. 2,816 car-bicycle accidents were recorded with this symbol. In 2,805 accidents, the right-turning road users were car drivers. These accidents corresponded to the scenario R20 (as defined in section 3.3 and demonstrated in Figure 3-7). In the other accidents with symbol 56, the right-turning road users were cyclists. The corresponding accident scenario was T5 (as demonstrated in Figure 3-7). In this way, just according to the road user types of the right turning one in accidents, accidents with symbol 56 were categorized into scenario

R20 or T5.

The second frequent used symbol was Symbol 17. Its proportion in the database was 12%, half of that of Symbol 56. This symbol concerns a left-turning road user and a through one. The left-turning one is responsible for accidents. 1,606 accidents with symbol 17 were recorded. In 1,463 accidents, the left-turning road users were car drivers and their causes were *mistakes made when turning* (Cause Nr. 35). The corresponding scenario was L12, as demonstrated in Figure 3-7. In this scenario, the road users are under control of the right of way. The left-turning road users were cyclists in the other accidents with symbol 17. These accidents were categorized into the scenario T15, as demonstrated in Figure 3-7. In this scenario, the direct left-turning cyclist has to yield to the through cars. In these accidents, the most common cause of cyclists was also *mistakes made when turning* (Cause Nr. 35). The accidents with symbol 17 were classified into scenarios L12 or T15, depending on the road user types of the left-turning one.

Like accidents with symbol 17, the accidents with symbol 89, which was ranked in the eighth place in terms of the accident frequency as shown in Figure 3-6, were also distinguished between scenarios L12 and T15. In this symbol, the through moving road user is the at-fault one. 290 accidents were recorded. In 277 accidents, the through moving one was the cyclist. These accidents corresponded to the scenario L12. They occurred due to the cyclists´ red-light-violation (Cause Nr. 31), when the diagonal green arrow light was on for the left-turning cars to finish their turning. This scenario is denoted as L12_1 in Figure 3-7. In the other 13 recorded accidents, the through road user was the car driver. They corresponded to the scenario T15.

The third frequent symbol was Symbol 50. It involves collisions between a road user and the cross traffic from the right or from the left. The symbols 49 and 15, which were ranked in the 4th and 7th places in terms of accident frequency as shown in Figure 3-6, represent the same situation as the symbol 50, i.e. collisions between the cross traffic. The difference is that the at-fault road user is from the left in symbol 50, from the right in the symbol 49 and both road users are responsible for the accidents in symbol 15. The accidents with these three symbols were mainly caused by the red-light-violation (Cause Nr. 31) of cyclists or car drivers. Another common cause was *mistakes made when entering the flow of traffic* (Cause Nr. 37). Regarding this cause, cyclists might illegally merge into the motorized traffic at intersections from the roadside or bicycle facilities, while car drivers might enter or exit from the properties or parking lots. Besides the three symbols, a number of other symbols are also related to collisions between the cross traffic. All symbols involving the cross traffic are shown in Appendix 3.3. The road users in these symbols could move through intersections or turn. In some symbols, more than two road users might be involved. 48% of accidents were caused by the red-light-violation, and 32% were caused by the cause Nr. 37.

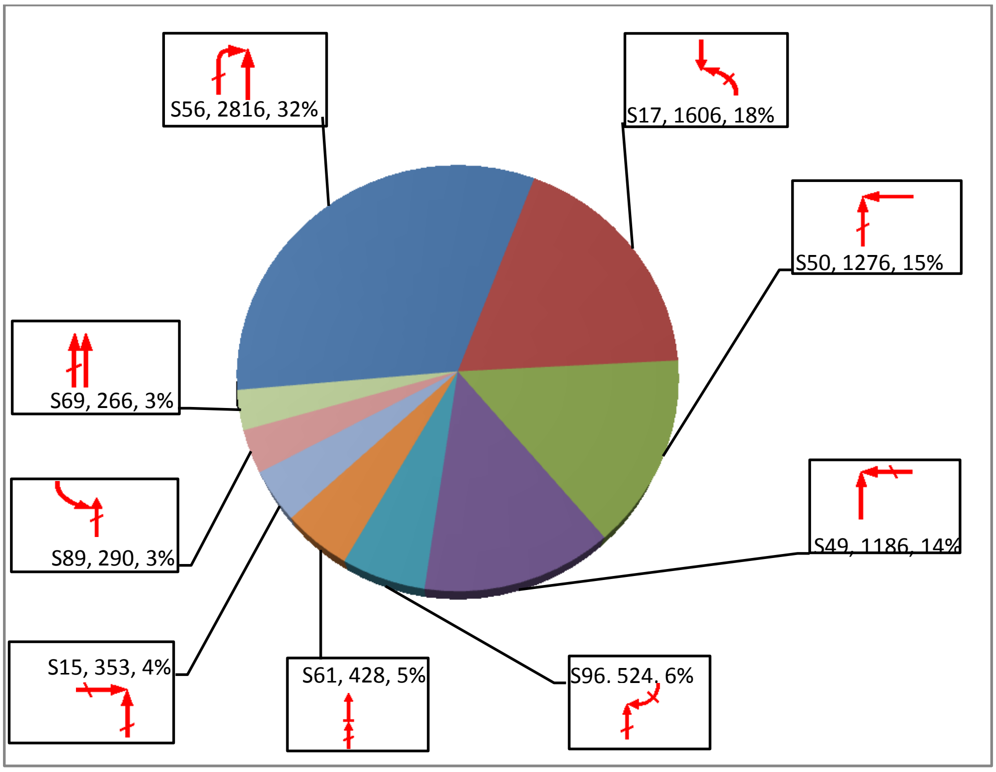


Figure 3-6 Distribution of common symbols. The symbol icons, symbol Nr., numbers of accidents, percentages among all accidents are presented. (self-made figure according to [34])

Another common symbol was Symbol 96. In all the recorded 524 accidents except two, the right-turning road users were car drivers. They corresponded to the scenario R17, i.e. collisions between right turning cars and through bicycles from the opposite direction on the same roadside, as demonstrated in Figure 3-7. In this scenario, cyclists are running in the wrong direction and yet have the right of way.

Accidents with symbol 61 and symbol 69 took place also frequently. The two symbols both concern two road users that move straight through intersections, and correspond to the scenario T20, as demonstrated in Figure 3-7. The two road users follow one another in symbol 69 and go in parallel in symbol 61. The police-recorded database included car-bicycle accidents inside signalized intersections contoured by the stop lines as well as within the boundary of one house number before and after intersections. Because the scenario T20 does not involve the turning road users, the recorded accidents might take place inside, before or after intersections. By integrating the accidents in the geographical map according to the accident geographical coordinates and the rotation angles, it could be easily determined where each accident exactly occurred. Among the 428 recorded accidents with symbol 61, 28 happened inside intersections, while 41 of 266 accidents with symbol 69 took place inside intersections.

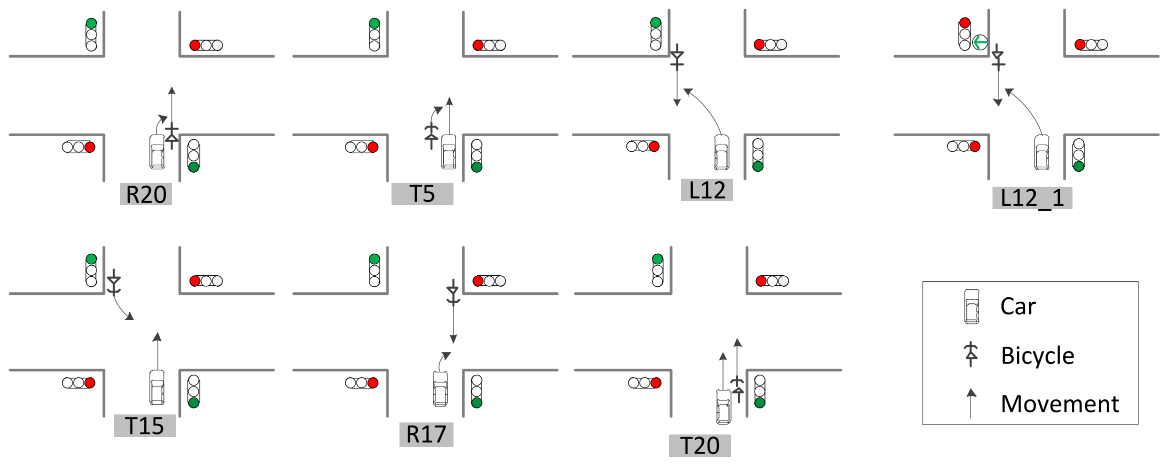


Figure 3-7 Car-bicycle accident scenarios which correspond to the most frequent symbols in police-recorded data. These scenarios concern the movement direction, the relative location of the car and the bicycle, as well as the states of the traffic signals.

In a similar way as the accidents with the above common symbols were classified into corresponding accident scenarios, the accidents with other symbols were also categorized combining the recorded accident variables, such as road user types, accident causation and geographical locations. Table 3-1 shows the classification results. It is observable that some symbols could be classified into more than one scenario. For example, the same set of symbols was incorporated into the scenarios L12 and T15, and the road user types were used to distinguish an accident between L12 and T15. Besides the normal scenarios defined in section 3.3, scenarios that involve only one road user (i.e. *single accidents*), road users who back up or turn over, and the stationary (or parked) vehicles are also included.

As Table 3-1 shows, R20 is the most frequent accident scenario. 3,624 accidents of the type R20 were recorded, accounting for 27.8% of all accidents. The high frequency of R20 accidents is mainly due to the problem of "blind spot", related to the motorists´ constricted visibility. Motorists´ visual behavior can help understanding causal factors in this kind of accidents. Car drivers´ visual interaction with bicycles in this scenario is studied and discussed in Chapter 4. Some accidents of R20 occurred because cyclists run a red light that was specifically designated for bicycles, while the traffic light for the motorized vehicles was at the same time green. Cyclists´ violation of red lights for bicycles may be due to the design of bicycle-specific traffic lights, such as their visibility, their coordination with other traffic lights and cyclists´ adaption to them. Studies in this field are very few and it deserves more researches, given that the use of bicycle-specific lights is being strengthened according to the German road plan.

The second most frequent scenario involved the cross traffic (from the right or from the left). Accidents of this scenario mainly occurred as the consequence of the red-light-violation (in 48% of 3,154 accidents) and illegal entries into the traffic flow (in 32% of accidents). The remaining 20% of cross-traffic accidents were attributed to various other causes. Following this scenario in frequency was the scenario L12, involving a left-turning car and a through moving bicycle from the opposite direction. 2,034 accidents of L12 were recorded. Accidents of L12 might occur, when the cyclist and car driver were both facing green lights. In this situation, car drivers were obliged to observe the existence of the bicycle and give the right of way. A considerable number of accidents of

L12 happened, when the traffic light was red for the through traffic, including for the through bicycles, and the diagonal arrow light for cars to finish left-turning was green. In these accidents, the cyclists were responsible due to red-light-violation. The scenario T20, another frequent scenario, accounted for 1,870 accidents. Accidents of T20 took place between a through bicycle and a through car that were going in parallel or following one another. The recorded accidents occurred inside, before or after intersections. In addition, 886 accidents corresponded to the scenario R17. This scenario depicts a right-turning car and a through bicycle on the same roadside but in the wrong direction. Despite of the illegal behavior of cyclists (riding in the wrong direction), the car drivers are obliged to give the right of way to the cyclists in this scenario.

Table 3-1 Symbol classification into accident scenarios and numbers of accidents of different scenarios

Scenarios	Car motion	Bicycle motion	Symbol Nr.	Accident number (Proportion)
R20	right turn	through	13, 18, 24, 56, 98, 111, 112, 133, 139, 146, 158, 110, 115, 154, 182	3,624 (27.8%)
Collisions between the cross traffic	through, right turn or left turn	through, right turn or left turn	6, 8, 14, 15, 16, 27, 28, 30, 38, 44, 49, 50, 52, 60, 73, 90, 91, 97, 116, 118, 135, 138, 140, 142, 143, 151, 155, 159, 165	3,154 (24.2%)
L12	left turn	opposing through	10, 17, 34, 89, 94, 132, 161, 167, 176, 185	2,034 (15.6%)
T20	through	through	5, 11, 12, 35, 45, 51, 61, 67, 75, 120, 141, 156, 175 (parallel); 64, 69, 70, 71, 72, 84, 108, 121, 124, 126, 130, 157 (lateral)	1,870 (14%)
R17	right turn	opposing through in wrong direction	76, 96, 101, 137, 163, 174	886 (6.8%)
Collision concerning stationary traffic	-	-	3, 36, 2	346 (2.7%)
T10	through	left turn	48, 63, 66, 85, 92, 95, 107, 134, 144, 148, 150, 162, 164, 194	281 (2.2%)
L9	left turn	through in wrong direction	48, 63, 66, 85, 92, 95, 107, 134, 144, 148, 150, 162, 164, 194	249 (1.9%)
T15	through	opposing left turn	10, 17, 34, 89, 94, 132, 161, 167, 176, 185	182 (1.4%)
Collisions concerning backing up or turning over	-	-	53, 54, 55, 57, 58, 59, 86, 87, 100, 122, 149, 168, 177, 190, 192	148 (1.1%)
L10	left turn	left turn	7, 21, 25, 77, 80, 104, 128, 102, 103	95 (0.7%)
Single accident	-	-	32, 39, 42, 43, 421, 321, 401, 791	45 (0.3%)
R5	right turn	right turn	78, 81,105,129,127	39 (0.3%)
T5	through	right turn	13, 18, 24, 56, 98, 111, 112, 133, 139, 146, 158, 110, 115, 154, 182	25 (0.2%)
L20	left turn	through	48, 63, 66, 85, 92, 95, 107, 134, 144, 148, 150, 162, 164, 194	15 (0.1%)
R15	right turn	opposing left turn	22, 82, 195	11 (< 0.1%)
L15	left turn	opposing left turn	20, 37, 113	11 (< 0.1%)
L1	left turn	opposing right turn	22, 82, 195	10 (< 0.1%)
R10	right turn	left turn	4, 23, 173	8 (< 0.1%)
T17	through	opposing through in wrong direction	31, 47, 68, 65, 88, 99	2 (< 0.1%)
L5	left turn	right turn	4, 23, 173	1 (< 0.1%)
Total				13036

3.4.2. Accident causation

A list of accident causes is widely used in the accident recording in Germany. It is also applied by the Berlin police-reported accident data. This list consists of 79 causes as presented in Appendix 3.1. All these causes are classified into the following five categories: *driving fitness*, *improper driving*, *technical or maintenance faults*, *improper behavior of pedestrians* and *general causes*.

The *improper driving* is further classified into different events (i.e. sub-categories) in relation to *use of road*, *speed*, *distance*, *overtaking*, *driving fast*, *driving side by side*, *priority and precedence*, *turning*, *U-turn*, *reversing*, *entering the flow of traffic, starting off the edge of the road*, *improper behaviors towards pedestrians*, *stationary vehicles and safety measures*, *failure to observe lighting regulations*, *load and number of passengers* and *other mistakes made by drivers*. The *general causes* refer to *road surface conditions*, *influence of the weather* and *obstacles*.

In the applied police database, car drivers were mainly responsible for 59% of accidents, while bicyclists were mainly responsible for the other 41% of accidents. The road users who are mainly responsible, i.e. at-fault road users, are the persons who are chiefly to blame for the accidents in the opinion of the police. At least one cause is documented for an at-fault person. More than one road user might be responsible for an accident. Causes are attributed to car drivers and bicyclists in different frequencies as shown in Figure 3-8.

For car drivers, the most common cause was *mistakes made when turning* (Cause Nr. 35 in Appendix 3.1). It resulted in 5,692 accidents (68% among the applied police database). This cause often concerns a turning car and a bicycle travelling in the same or opposite direction (, when both are assigned a green signal phase). In accordance with the traffic law, the car has to give the right of way to the bicycle in such a situation. Therefore, once the two parties collide with each other, the car driver should first be to blame. Regarding the accident scenarios, accidents due to this cause often occurred between a right-turning car and a through bicycle in the same direction, i.e. scenario R20 as defined in section 3.3 (amounting to 49% among all accidents caused by car drivers with cause Nr. 35), between a left-turning car and a through bicycle from the opposite direction, i.e. L12 (amounting to 26%), and between a right-turning car and a through bicycle from the opposite direction in the wrong direction i.e. R17 (amounting to 9%),. In these accidents, the car drivers´ mistake might be that they do not perceive the presence of bicycles or incorrectly predict the trajectories of bicycles.

The second most common accident cause by car drivers was *failure to observe the traffic control by traffic light* (Cause Nr. 31). Red-light-violation is the most overt illegal behavior at signalized intersections, and is a popular safety problem all over the world, since it concerns high-speed and high-severity collisions. 29,101 red light violations of motor vehicles were observed in Berlin in 2014 [168]. 7% (584) of accidents occurred due to this cause in the applied police data. Red-light-violation has been studied in a great number of researches. The study results have suggested that red light runners were more likely to be younger, male and risky drivers who had poorer driving records and less frequently wore seat belts [169-172]. Higher daily traffic volumes were suggested to be related to more red light running behaviors [173,174]. In order to decrease red light violation, timing the light cycle was regarded as one of the best engineering treatments. For example, by properly increasing the duration of the amber and red light intervals, the number of red light runners might be decreased [175,176]. Other engineering treatments to decrease red light violations, such as improving the signal visibility, reducing speed limit near intersections and improving consecutive signal coordinates, were also suggested [177]. In addition to the engineering treatments, enforcement cameras have been installed and demonstrated to be effective to decrease red light violations [177,178]. Since the red-light-violation of car drivers has come under the focus of researchers, the relevant knowledge is continuously enhanced leading to improved treatments to decrease red light violations in practice.

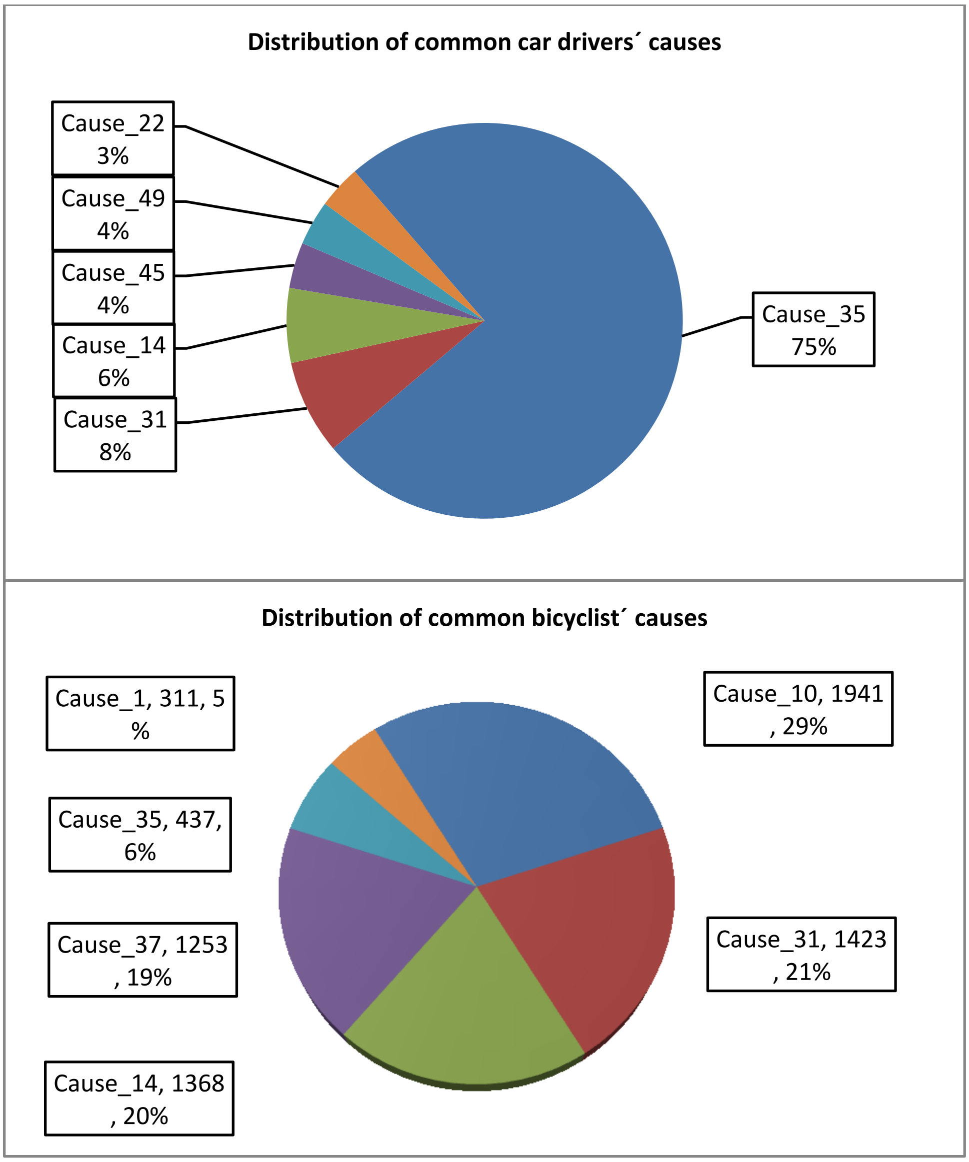


Figure 3-8 Distributions of common causes: Cause No., accident numbers and accident percentages. The common causes are: Cause 35, mistakes made when turning; Cause 31, failure to observe the traffic control by policemen or traffic lights; Cause 14, insufficient safety distance; Cause 45, behavior contrary to traffic regulations when getting on or off a vehicle, loading or unloading; Cause 49, other mistakes made by driver; Cause 22, other mistakes made when overtaking; Cause 10, use of wrong carriageway (or lane) or unlawful use of other parts of the road; Cause 37, mistakes made when entering the flow of traffic; Cause 1, influence of alcohol.(self-made figure according to [34])

Another common accident cause by car drivers was *insufficient safety distance* (Cause Nr. 14). It corresponded to 461 accidents (6%). *Insufficient safety distance* often caused accidents in cases where a car was following a bicycle on the intersection entering approach. A disadvantage of traffic signal control is that it can lead to increases in rear-end accidents due to the cyclical stopping of traffic [17]. This leads not only to accidents between motorized vehicles but also to accidents between motorized vehicles and bicycles. Besides, *insufficient safety distance* also often caused accidents when a car was running in parallel to a bicycle while crossing intersections. This might be due to the intersection space limitation as well as the improper behavior of drivers.

Following this cause, other common causes included:

- *behavior contrary to traffic regulation when getting on or off a vehicle, loading or unloading* (Cause Nr. 45) under the sub-category *stationary vehicles and safety measures*,
- *other mistakes made by driver* (Cause Nr. 49) under the sub-category *load and number of passengers,*
- *and other mistakes made when overtaking* (Cause Nr. 22) under the sub-category *overtaking*.

The most common cause by cyclists was *use of wrong carriageway (or lane) or unlawful use of other parts of the road* (Cause Nr. 10). Cyclists made this kind of mistake in 1,941 accidents (26% among the applied police database). This cause mainly concerned the following situations: a bicycle running in the wrong direction collided with a (right- or left-) turning car; a bicycle that was using other road parts outside the bicycle crossing collided with a turning car; a bicycle running in the wrong direction collided with a car that run against the red light. However, in these scenarios, the turning car, which had to give the right of way to the bicycle or run against the red light, rather than the bicycle, should be mainly responsible for the accidents.

For cyclists, the second most common cause was also the red-light-violation. In car-bicycle accidents, red light violations by cyclists caused more accidents than by car drivers: 1,423 (19%) to 584 (7%). Studies on cyclists´ red-light-violation have received attention only in recent years. The popular method was based on installed cameras at intersections. The cyclists were subdivided into three distinct types according to their behaviors facing red lights: those who stop and wait until the red light turns green (law-obeying), those who stop but do not wait until the light turns green (opportunistic) and those who never stop when the light is red (risk-taking) [179,180]. These studies have showed that the male cyclists were more likely than the female to run the red light, and the younger more likely than the older [181]. While cyclists were less likely to run the red light, when other cyclists were also present [182,183], the probabilities of red-light-violation were increased, when no or fewer cyclists were waiting and even when other cyclists were already crossing the red [184]. In addition, the likelihood of red-light-violation was found to be related to the red light duration [181].

Red-light-violation of cyclists mostly caused collisions between bicycles and the cross traffic. There were two common exceptional collision scenarios. The first occurred when a bicycle that ran the red light collided with a left-turning car from the opposite direction. This kind of accidents occurred at intersections where a diagonal green arrow light was installed. The diagonal green light allows the left-turning cars who have already entered in the intersection to finish their left turning after the red light in their direction is on. Another occurred between a bicycle that ran the red light and a right-turning car in the same direction. In this situation, the lights that bicycles ran were bicycle-specific traffic lights. The cycle of bicycle traffic lights is coordinated with the normal traffic lights for motorized vehicles: they often turn red from green several seconds prior to the normal lights and turn green from red several seconds earlier than the normal lights. This aims to avoid the conflicts between through bicycles and right-turning vehicles. According to the German Road Traffic Regulations, as a transitional regulation, bicycles should follow the normal traffic lights for motorized vehicles since 01.04.2013, when no bicycle traffic lights are present. With the popularity of bicycle traffic lights, it deserves more attention to study the factors related to the bicycle-traffic-light-violation. In particular, factors that the installation of bicycle traffic lights itself brings about should be noticed, such as the visibilities of traffic lights, their coordination with other traffic lights and road users´ adaption to them. At present, only one of the reviewed studies has focuses on the compliance at bicycle-specific traffic lights [185].

The third most common cause by cyclists was *safety distance* (Cause Nr. 14). It resulted in accidents due to insufficient lateral or longitudinal distance. The next common cause was *mistakes made when entering the flow of traffic (e.g. from premises, from another part of the road or when starting off the edge of the road)* (Cause Nr. 37). Those mistakes were primarily related to cyclists´ merging into the motorized traffic flow from bicycle paths, bicycle lanes, sidewalks or just from the rightmost of roads. Another common cause is *mistakes made when turning* (Cause Nr. 35). It mainly concerned bicycles that failed to change lanes to the right side of roads in advance while right-turning and that failed to give the right of way to the through motorized vehicles from the opposite direction while direct-left-turning. *Influence of alcohol* (Cause Nr. 1) is also a common cause. This cause was documented as an indirect cause, and always recorded with other causes for an accident.

3.4.3.Accident consequences

The variable describing accident consequences is "*categories of accidents*" in the database. There are six categories of accidents. They are numbered according to the person or material damage severity (the smaller category number represents the higher severity):

- *Accident with persons killed* (category1)
- *Accident with seriously injured persons* (category 2)
- *Accident with slightly injured persons* (category 3)
- *Severe accidents involving material damage in narrow sense* (category 4)
- *Other accident involving material damage* (category 5)
- *Other accident involving material damage under the influence of intoxicating substances* (category 6).

The later three categories (i.e. categories 4, 5 and 6) are related to only material damages, whereas the first three categories (i.e. categories 1, 2 and 3) are related to casualties, i.e. persons injured or killed in accidents. In the categories of accidents, the injury severity of casualties is defined as follows:

- Person killed: persons who died within 30 days as a result of the accident
- Person seriously injured: persons who were immediately taken to hospital for inpatient treatment (of at least 24 hours)
- Person slightly injured: the other injured persons.

In the applied police database, the accident consequences are available only for the accidents in 2013. Thus, the following analysis concerning accident consequences is based on the accident data in 2013.

1,043 car-bicycle accidents at signalized intersections were recorded in 2013. Among them, 34% (474) resulted in only material damages, while 66% (929) involved casualties. With regard to the injury severity of the casualties, 89.8% were slightly injured, while 10% were seriously injured. No person was killed.

In addition, 98 of 99 casualties in category 2 and 850 of 874 casualties in category 3 were bicyclists, respectively. That is to say, 97% of casualties in the recorded car-bicycle accidents were bicyclists. This figure confirms the vulnerability of bicyclists.

3.4.4. Accident distribution over months

The distribution of car-bicycle accidents at signalized intersections over months (averaged over eleven year) is showed in Figure 3-9. The peak values of accident numbers (170 accidents) were recorded in August and September, followed by that in June (157) and July (154). A large number of accidents were also reported in October (133) and May (129). The accident numbers in these months were larger than the average value (110). Comparatively, fewer accidents (than the average value) were reported in January, February, December, March and November.

The general bicycle accident database (all bicycle accidents with any other road users at any road location) suggests that bicycle use is greatly season-relevant and consequently results in much more bicycle accidents in spring and summer months [162]. The season of spring in Berlin starts normally between March and May, accompanied by better weather conditions, higher temperature and longer days. The season of summer ends normally between October and November. The distribution of car-bicycle accidents at signalized intersections is consistent with that of the general bicycle accident database. It suggests that the occurrence frequency of car-bicycle accidents at signalized intersections is also influenced by the season, because of the changing bicycle traffic volume.

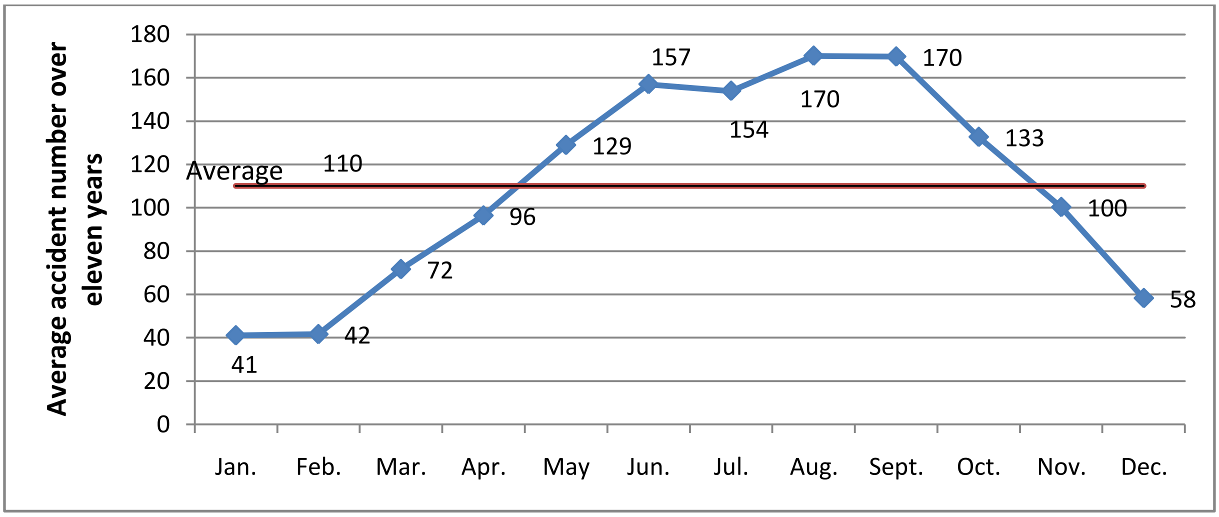


Figure 3-9 Distribution over month of car-bicycle accidents at signalized intersections in Berlin, averaged over 2003 to 2013 (self-made figure according to [34])

3.5. Accident analysis based on GIDAS database

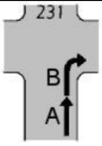
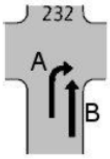
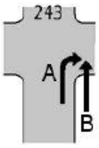
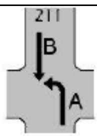
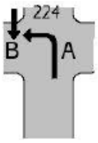
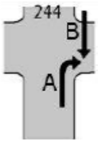
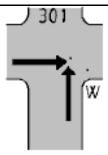
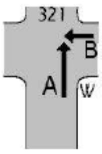
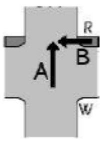
GIDAS accident data is regarded as being representative for German. The selective perception is based on the existing statistically representative sampling and revision of the data set [159]. In this section, the accidents in GIDAS were analyzed and assembled into scenarios as described in section 3.3. The analysis comprised car-bicycle accidents at signalized intersections between 2005 and 2013. Totally 469 accidents were covered in this database.

"*The type of accident*", one of the variables to document accidents, is defined according to movement directions, relative locations, and the road environment (e.g. road layouts, traffic controls, the presence of bicycle paths. In GIDAS data, "*the type of accident*" is recorded with three-digit codes. Thus, it is directly usable to class accidents into representative scenarios. There are seven categories of accident types. They are *driving accident*, *accident caused by turning off the road*, *accident caused by turning into a road or by crossing it*, *accident caused by crossing the road*, *accident involving stationary vehicles*, *accident between vehicles moving along in carriageway and other accidents* [13]. Every category consists of a number of accident types, ranging from thirty-two to fifty-four. The majority of accidents in this database do exist under the following two categories of accident types: *accident caused by turning into a road or by crossing it* and *accident caused by crossing the road*. The GIDAS codebook documents detailed information for all accident types. Like the accident symbols in the police-recorded database, the accident types are also illustrated by arrows, which represent the road users, as shown in Table 3-2. According to the type of accident, the accidents were classified into the corresponding scenarios with the help of experts on GIDAS data. The classification results are recorded in Appendix 3.4.

Table 3-2 presents the first four most frequent scenarios and their corresponding accident types. The most frequent accidents corresponded to scenario R20, accounting for 19% of accidents in the applied GIDAS database. The second most frequent scenario was L12, involving a left turning car and an oncoming bicycle from the opposite direction. Sixty-nine accidents of L12 were recorded, coming up for 15% of all accidents. Following L12 was the scenario R17 with a share of 13%. This scenario occurs between a right turning car and an oncoming bicycle on the same roadside but in the wrong direction. The scenario T11 was the fourth most frequently recorded scenario. It is one of scenarios that involve the cross traffic. When all the accidents involving the cross traffic (i.e. T11, T16, T13, T18, L16, R16, R11and L11) were added up, the accident number was up to 175. The share among all accidents was 37%, even higher than the scenario R20. However, it was much lower, compared with the share of 76% based on the German Insurance Association. This might mainly be derived from the control of traffic lights, which could eliminate the conflict points between the cross traffic. Although the GIDAS accident causes were unavailable for this study, the information contained in the variable of "*the type of accidents*" indicated that bicycles´ illegal merging into the motorized traffic flow caused 19% (34) of the accidents involving the cross traffic. The most causes were supposed to red light violations for the other accidents

This scenario analysis result was generally similar to that based on the Berlin police-reported data with respect to the first four most common scenarios, except that accidents of T20 account for a much larger proportion in the police-reported data. The reason might be that accidents within the boundary of one house number before and after intersections have also been considered as the accidents at intersections in the police database.

Table 3-2 The first four most frequent accident scenarios, their corresponding accident types and accident numbers

Scenarios	Types of accident (Diagram, Nr. and motion)	Accident numbers
R20	 231: Right turning and longitudinally following  232: Right turning and laterally following  243: Right turning and bicycles from bicycle paths from the same direction	91 (19%)
L12	 211: Left turning and oncoming straight  224: Left turning and oncoming bicycles from bicycle path	69 (15%)
R17	 244: Right turning and oncoming bicycles from bicycle paths	61 (13%)
T11	 301: Privileged from the right and waiting-required straight  321: Privileged from the right and straight  344: Privileged bicycles from bicycle paths from the right and straight	53 (11%)

3.6. Conclusion and discussion

To know accidents is necessary for accident prevention. Given that accident analysis particularly focusing on car-bicycle accidents at signalized intersections is absent in the past studies, this chapter analyzed two databases to explored the characteristics of car-bicycle accidents at signalized intersections.

The accident scenario is a widely used accident category for accident analysis. Car-bicycle scenarios at signalized intersections were first defined by the geometrical configuration as well as the road layout. Based on this scenario definition, two accident databases were analyzed concerning scenarios. They were the Berlin police-reported accident data over eleven years (13,036 accidents) and the GIDAS accident data over nine years (469 accidents).

The analysis results of scenario frequencies based on the two databases were similar. The most common scenario was a right-turning car colliding with a through bicycle in the same direction (i.e. scenario R20) with a share of 28% in the Berlin police database and 19% in the GIDAS database. The next three most common scenarios included collisions between a left-turning car and an oncoming bicycle, between a through car and an oncoming bicycle in the wrong direction, and between a through car and a through bicycle in the same direction. These scenarios were normally controlled under the right of way.

Based on the police database, the accident causes were analyzed. For car drivers, the most common cause was mistakes in their right turning. During right turning, car drivers were most of time obliged to yield to the conflicting cyclists under the control of the right of way. Once accidents happened, it should be car drivers´ responsibility. For cyclists, the most common cause was their unlawful use of roadways, including running in the wrong direction and using other parts outside the bicycle crossing in crossing intersections. Red-light-violation was the second most frequently recorded accident cause for both car drivers and cyclists. Red-light-violation of car drivers or cyclists amounted to 48% of accidents involving the cross traffic (12% among all accidents).

Based on the police database, the accident consequences and time were also briefly analyzed. The vulnerability of cyclists in road traffic is highlighted by the large amount of 97% of bicyclists´ casualties within the overall number of recorded accidents. The frequency of car-bicycle accidents at signalized intersections over months was found to be strongly influenced by the season because of the change in bicycle traffic volume.

Considering that Berlin is a bicycle-friendly city with a high bicycle modal share, and GIDAS accident data is regarded as being representative for German that is in the top three of European countries in terms of bicycle use, the analysis of the two databases presents a typical picture of car-bicycle accidents at signalized intersections in a bicycle city/country.

Furthermore, the analysis results reveal implications for possibilities to decrease accidents. As indicated by the two databases, the most common car-bicycle scenario was the scenario R20. This scenario could be specifically focused on in studies, in order to find out e.g. how accidents of this scenario happen and what can be done to decrease the risk of this scenario. Following this implication, how car drivers detect and observe cyclists in the scenario R20 was studied in Chapter 4, by analyzing the eye movement data of car drivers collected in a Quasi-NDO study. Another important implication concerns red-light-violation. For both car drivers and bicyclists, the second most frequently recorded accident cause was red-light-violation. Red-light-violation could cause not only lateral accidents, which is well-known and has been studied in many researches, but also longitudinal accidents. A longitudinal scenario caused by red-light-violation was a collision between a left-turning car and an oncoming bicycle. It occurred at intersections where the diagonal green arrow was installed. When the green arrow was lightened, the oncoming bicycles lose the priority, and the cars were protected for their left turning. Another longitudinal scenario involved a right-turning car and a through bicycle in the same direction. It occurred, when cyclists violated the red light of the bicycle-specific traffic signal rather than the general traffic signal for motorized traffic. In Germany, the installation of bicycle-specific traffic lights is advocated and their deployment is being extended. More accidents of this scenario are expected. More attention and studies for bicycle-specific traffic light violation are suggested in future research work, e.g. on the aspects of light design, visibility, coordination with other traffic lights and road users´ adaption to the lights.

In addition, the frequencies of accidents of different scenarios provide necessary statistics for the studies in Chapter 4 and Chapter 5. In Chapter 4, they were compared with the frequencies of the collected car-bicycle conflict of different scenarios. In Chapter 5, they were used to measure the objective risk of different scenarios and compared with the subjective risk.

4. Study of car driver-bicyclist interactions at signalized intersections by a Quasi-NDO study

The potential to understand accident causality based on historical accident data analysis is limited, due to the lack of detailed information on the chain of events preceding an accident. The use of traffic conflicts is gaining acceptance as a surrogate for accident data analysis for safety diagnosis, as traffic conflicts can provide deeper insight into the failure mechanism that leads to accidents [26]. The traditional way to collect conflict data relies on human observation, challenged on several issues regarding the repeatability and consistency of results [27]. With the development of information technologies, Naturalistic Driving Observation (NDO) datasets that combine cameras, radars, eye-tracking devices and other sensors are now advocated and proved to be reliable and efficient to capture, store and analyze traffic conflicts [26,28]. Although there are considerable NDO studies with various focuses, such as distraction, fatigue or drowsiness, driver characteristics, and interactions between passenger cars and heavy vehicles etc., few NDO studies investigated particularly interactions between car drivers and bicyclists at signalized intersections. Several Naturalistic Cycling Observation (NCO) studies have been done to investigate interactions between car drivers and bicyclists, but from perspective of bicyclists [105-107]. The analysis based on the Berlin police-reported accident database indicates that car drivers took main responsibility in more car-bicycle accidents at signalized intersections than bicyclists did: 59% to 41%.

This chapter develops a technical framework to study interactions between car drivers and bicyclists at signalized intersections from perspective of car drivers. A car is instrumented with various sensors and used to record car drivers´ driving behaviors, including car-operation behaviors, body movements and eye movements, as well as the environment. Car-bicycle conflicts are detected from the collected data using both automated method and manual method. The frequencies of conflicts are compared with that of accidents.

As documented in the literature review, eye movement data can provide evidence about visual attention in most cases, which is directly related to crash causality. Therefore, eye movements of car drivers are analyzed in their interactions with bicycles at signalized intersections. The aim is to investigate how car drivers detect and observe bicyclists at signalized intersections.

4.1. Methodology

4.1.1. Quasi-NDO: Data collection by an instrumented car

To study interactions between cars and bicycles, people could instrument a car or a bicycle. In other words, either a Naturalistic Driving study or a Naturalistic Cycling study could be carried out. In most car-bicycle conflict points at signalized intersections, the bicycle has the right of way following traffic rules. Just for this reason, car drivers are responsible for more car-bicycle accidents than cyclists are, as indicated by the accident causation analysis in Chapter 3. How car drivers react to bicycles is more safety-relevant in a car-bicycle conflict than how cyclists do. Consequently, a car was instrumented and car drivers´ behaviors were primarily recorded in this work.

In this study, participants were recruited to drive an instrumented car through a preset route. A researcher in the car directed the drivers to follow the route while data was collected. The car drivers´ behaviors and the driving environment were recorded. Compared with an ideal naturalistic driving study, where participants drive their own cars and can decide when and where to drive, and no observer is present in the car, there were some non-naturalistic factors in this study. However, whether the collected behaviors are natural or not depends on what the research question is [108]. This study focused on interactions between car drivers and bicyclists, i.e. car drivers´ reactions in respond to bicyclists. In the uncontrolled real traffic, participants´ interactions with bicycles were task-oriented. Participants were aware that there were real hazards of crashes with bicycles, and therefore had to observe the existence of bicycles, judge potential risks and conduct necessary reactions combining the driving environment. Thus, this study was to a certain extent naturalistic for the participants.

In the traditional methods for studying traffic behaviors, for example, in controlled experiments or simulator experiments, there is usually strict control over external confounding variables, and therefore they feature low ecological validity. In on-road studies or field experiments, participants are often instrumented to perform a specific behavior that is unrelated to driving task, such as talking on a cell phone, performing a cognitive task, etc [70,71]. In this study, contrary to the aforementioned, participants were exposed to the real traffic environment and were not assigned any specific task. Although there were some non-naturalistic factors in data collection, more naturalistic driving behaviors could be observed than in those traditional methods.

4.1.2. Participants

Considering both the basic study requirement and study resource limitation, 22 participants were recruited in this study. They were aged from 24 to 44 (Mean=31, Variance=5.6), and 20 men and 2 women were among them. These participants volunteered for this study and signed the informed agreement. All participants held valid driving licenses. The description of their individual driving experiences indicated that 30% of them drove at least three times every week, 40% four times every month, 15% twelve times every year and 15% seldom in the past year. Four participants were short-sighted and required to wear contact lenses instead of glasses, because the short-sighted glasses might obstruct the function of the eye tracking headset, one of data collection apparatus.

4.1.3. Equipments

(a) (b) (c)

Figure 4-1 Study equipments: Video Vbox (a), Eye tracking headset (b), GoPro camera (c)

As an important merit of NDO, it can address behavioral and situational aspects of an accident or a safety-critical situation. This merit depends on various sensors. They should record what happened inside and outside the car. With regard to interactions between cars and bicycles, the following data are of great interest: car drivers´ operational behaviors (i.e. car dynamic data), body movements, status of bicycles, relative positions between cars and bicycles, traffic signal phases, presence of other road users, etc. Particularly, eye movements are a significant indicator of road users´ attention. In recent years, eye movements are considered in many studies to identify crash causation. In this study, eye movements of car drivers were also included. To record data aforementioned, the following devices were equipped in the experiment car.

One of the measurement devices was RaceLogic Video VBox Pro (hereinafter VBox), as shown in Figure 4-1. The Vbox combined a GPS data logger and a four-camera video recorder [186]. The GPS data logger could record numerical data at a sampling rate of 10 Hz. The recorded data included GPS position (latitude, longitude and height), horizontal velocity, vertical velocity and heading. The GPS position measurement was generated with an accuracy of 2.5 m 95% CEP (Circle of Error Probable) and the velocity data was recorded with an accuracy of 0.2 km/h [186]. The video recorder recorded the driving environment at a constant rate of 25 fps. The measured numerical and video data could be automatically synchronized corresponding to the local time.

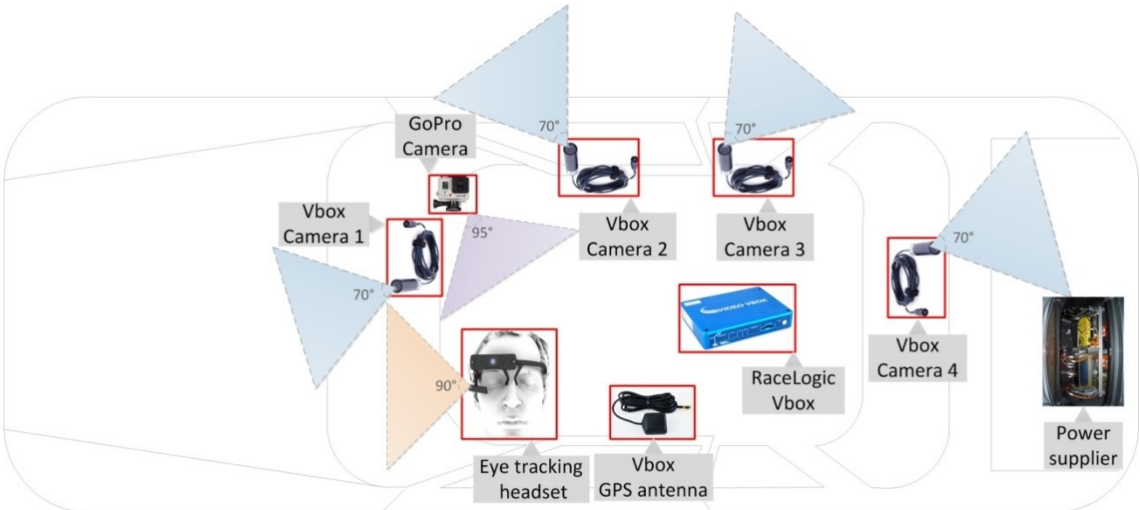


Figure 4-2 Layout of applied equipment

Another apparatus was the Pupil Labs eye tracking headset, as shown in Figure 4-1. The drivers wore it like a pair of glasses. This headset had two cameras: The infrared spectrum eye camera recorded the right eye movements of the users at maximum 30 fps; the high resolution (1920 x 1080) world camera recorded the scenes in the users´ forward field of view of 90° at maximum 30 fps. It could provide an average gaze estimation accuracy of 0.6 degree of visual angle [187]. In data collection, the two cameras were connected to a laptop. Both video streams were saved by use of the Pupil software that could map the pupil position from the eye to scene space. As a result, a video stream consisting of scenes in car drivers´ forward field of view and eye gaze locations, represented by a red circular cursor, was generated, as shown in Figure 4-3. The circular cursor corresponded to a 50 pixel diameter and was equivalent to about 3.6° visual angle.

A HD camera GoPro Hero 3+ was mounted in front of the front passenger seat facing the car driver. It was used to record the drivers´ body movements, including head movements and hand steering, as shown in Figure 4-3.

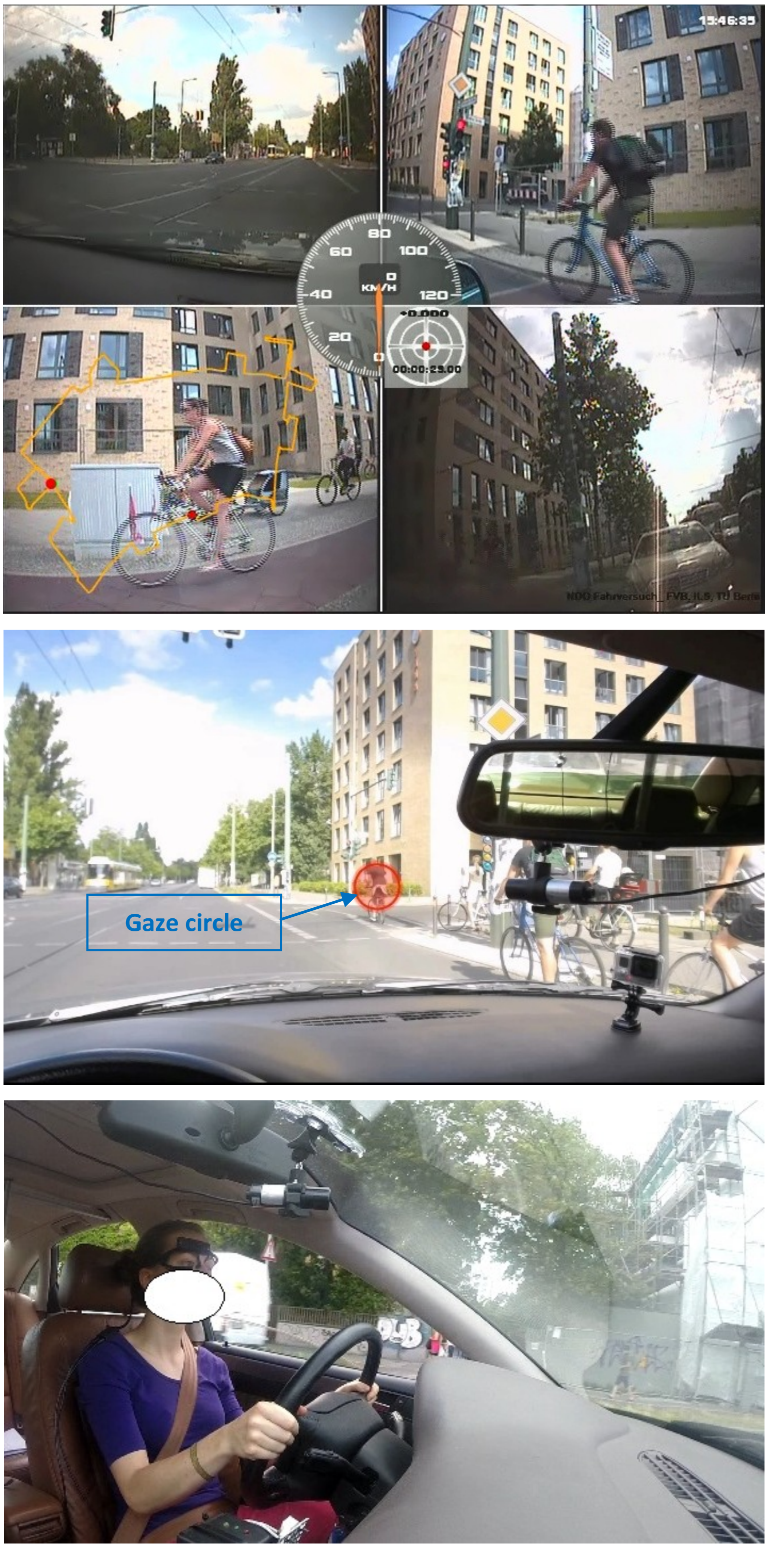


Figure 4-3 Video frames of VBox (top), eye tracking headset (middle) and GoPro camera (bottom)

The layout of the applied equipment in the instrumented car is shown in Figure 4-2. The VBox GPS antenna was mounted on the car roof to receive GPS signals, while the power supply set was mounted in the luggage boot. The four VBox cameras with the view angle of 70° were used to record the forward, right front, right rear and rearward views of the instrumented car. The world camera of the eye tracking headset recorded the drivers´

forward view. The GoPro camera recorded the scene on the left side and car drivers´ body movements. The suite of the six cameras offered a view of approximate 360° around the instrumented car, which greatly facilitated the future analysis of the driver behavior recording. Figure 4-3 shows the video views of the VBox, eye tracking headset and GoPro camera. The four VBox camera view windows were integrated in one video frame. The top left, top right, bottom left and bottom right windows corresponded to the forward, right front, right rear and rearward views of the car, respectively. In the center of the VBox video frame, a dashboard simulator displayed the real-time velocity and acceleration of the car. In the bottom left window, the real-time location of the car within the driving route was displayed in the driving route. The view frame of the eye tracking set showed the car drivers´ forward view with gaze locations.

4.1.4. Driving route

An 11 km long driving route was selected in the district of Mitte in Berlin, as shown in Figure 4-4. Unlike the predetermined occurrences in controlled experiments, the number of bicycles that would appear in the driving route was random. To obtain as many bicycle-meeting events as possible, the driving route covered roadways with high or mediate daily bicycle traffic density. The bicycle volumes at the primary signalized intersections in the driving route were measured during traffic peak time periods (7:30-9:45 a.m., 16:00-18:30 p.m.) on weekdays while good weather conditions prevailed. The measurement results (in bicycle volume/ 30 minutes) are shown in Figure 4-4.

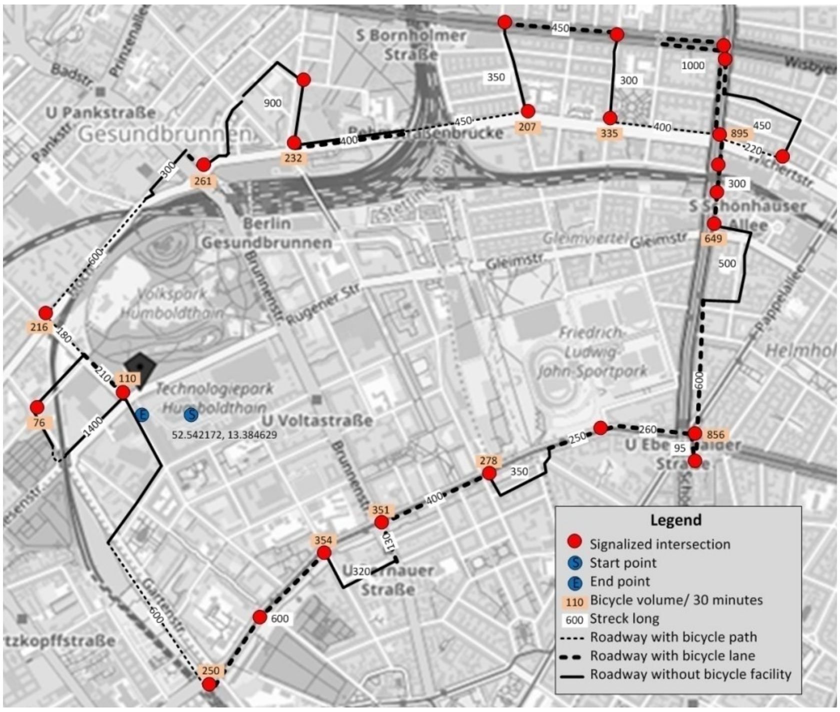


Figure 4-4 Driving route with the detailed route information

The selected route covered 25 signalized intersections. Fourteen right-turning, eight left-turning and six going-through traffic motions had to be executed at these intersections. The route covered different bicycle facilities. It included 2.45 km of roadways with bicycle lanes/protective lanes, 4.6 km of roadways with bicycle paths, and 4 km of roadways without specific bicycle facilities. The roadways with bicycle lanes had a traffic lane in each direction. Most of them were undivided roadways. Only 620 m were divided by central medians. The roadways with bicycle path had two traffic lanes in each direction. About one-half of them were undivided and the other half was divided by central medians. Roadways without bicycle facilities existed mainly in residential tempo-30-zone. They were mostly so narrow that only one direction of vehicle traffic could go through at the same time.

4.1.5. Procedure of data collection

The data collection was conducted in July and August 2014, representing the months with the highest number of bicycle accidents in Berlin [162]. The participants implemented the study in traffic peak periods on weekdays, ten of them in the morning peak time between 8:00, and 9:30 and twelve of them in the afternoon peak time between 16:00 and 17:30. Most driving took place in sunny or slightly overcast weather conditions, except that it rained unexpectedly during one set of data collection.

A sum of fourteen hours of data was collected. Each driving lasted averagely 45 minutes. Each individual participant spent at least two hours, including the pre-study preparation and post-study data management. Prior to the driving part, the participants were supplied with study information. After that, participants answered a pre-survey check to provide their personal information, such as age and driving experience. Subsequently, the eye-tracking headset was adjusted in accordance with the participants´ height, eye and face geometry, and calibrated with a printed calibration marker. The calibration was carried out at least two times for the purpose of higher calibration accuracy. In the data collection process, an instructor sat in the front passenger seat to direct the driving route to the drivers. The participants drove the car in their natural driving way without any specific tasks. After the data collection, participants were required to answer a post-survey questionnaire, mainly to report if the installed instrument or the study as such had influenced their driving behaviors.

4.2. Conflict detection

Accident events collected in NDO studies could supply most direct information to address accident causation. However, accidents are rare events. According to statistics, for an accident to happen an average driver would need to travel 62 million miles [110]. In such a small-scale study, no accidents were expected to be collected. Therefore, conflicts were interesting events in this study.

To detect and identify car-bicycle conflicts at signalized intersections in the collected data, two methods were applied: the automated conflict detection and the manual conflict detection. The automated conflict detection was based on a deceleration trigger. The deceleration trigger could automatically "pick" potential conflicts. However, video data should be reviewed to identify if they were real conflicts.

The manual conflict detection depends on video review combining dynamic data. Manual video observation is normally very time-consuming. To detect conflicts at signalized intersections, it was unnecessary to review all video frames. As described previously, the real-time car location in the driving route was displayed in the Vbox video frames. According to the car location displayed in the VBox video, the driving data at signalized intersections could be easily positioned. This saved a great amount of time, and supplied potential for the semi-automated method.

4.2.1. Automated conflict detection

A major application of naturalistic driving studies is the analysis of safety-critical events, including crashes and conflicts. Detection of safety-critical events in naturalistic driving data is currently mainly based on the appearance of extreme values of vehicular dynamics recognized via kinematic triggers [67,75]. The events activating kinematic triggers could be longitudinal or lateral decelerations, Time-To-Collision or yaw rates within a certain threshold, or a combination of them. Any trigger activation would consequently lead to automatic detection of possible safety-critical events.

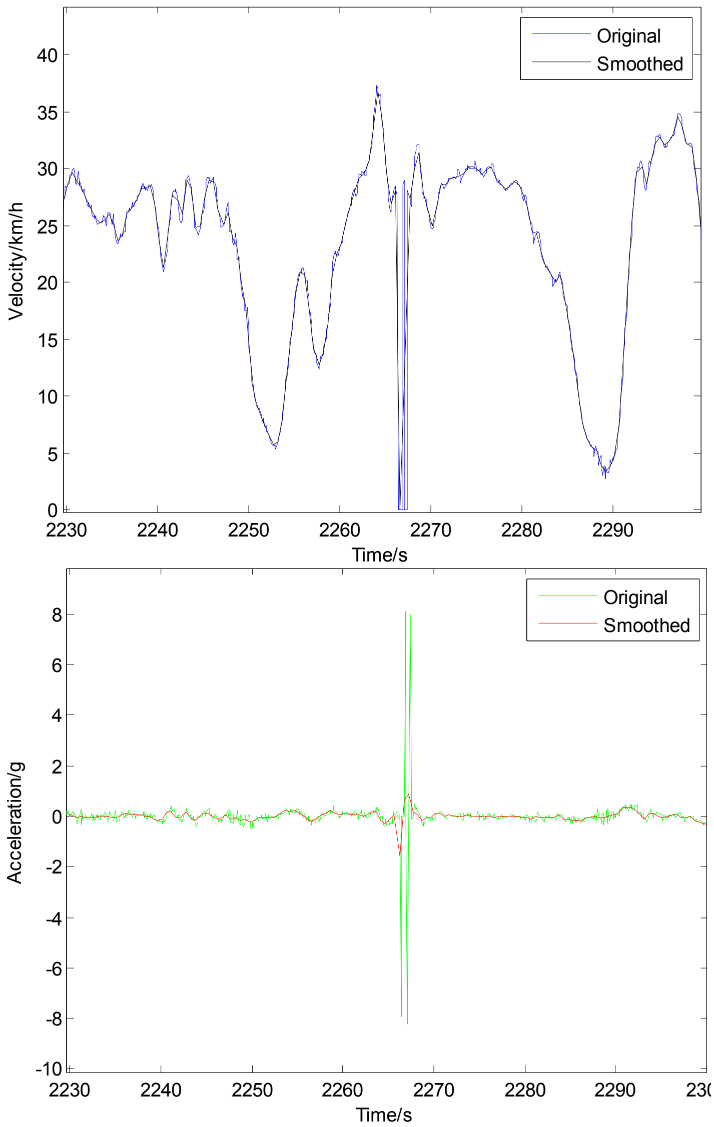


Figure 4-5 Example of original and smoothed velocity-time curve (top) and acceleration-time curve (bottom)

In data collection, velocities of the instrumented car were continuously recorded, from which decelerations/accelerations could be derived. The measured velocity value was highly accurate, and Kalman Filter already filtered the outputted data from VBox. However, there were two problems with the data, limiting its use in event detection. First, frequent vibration was observable in the velocity-time curves, with the vibration more obvious in the derived deceleration/acceleration-time curves, as shown in Figure 4-5. The frequent vibration primarily came from that it is impossible to keep absolute constant velocity or acceleration even for a very short time in reality. Second, the velocity data was mixed with noises: data missing (zero-noise) and abnormal extreme high or low values. The velocity data from VBox was measured by a speed-sensor that worked based on GPS signals using Doppler Effect. The environment could affect the GPS signals, generating measurement noises. Looking into the driving environment, the noises were usually generated when the car was driving past high buildings, under trees, under bridges, on uneven grounds and in bad weather [188]. These two kinds of noises could wrongly report safety-critical events.

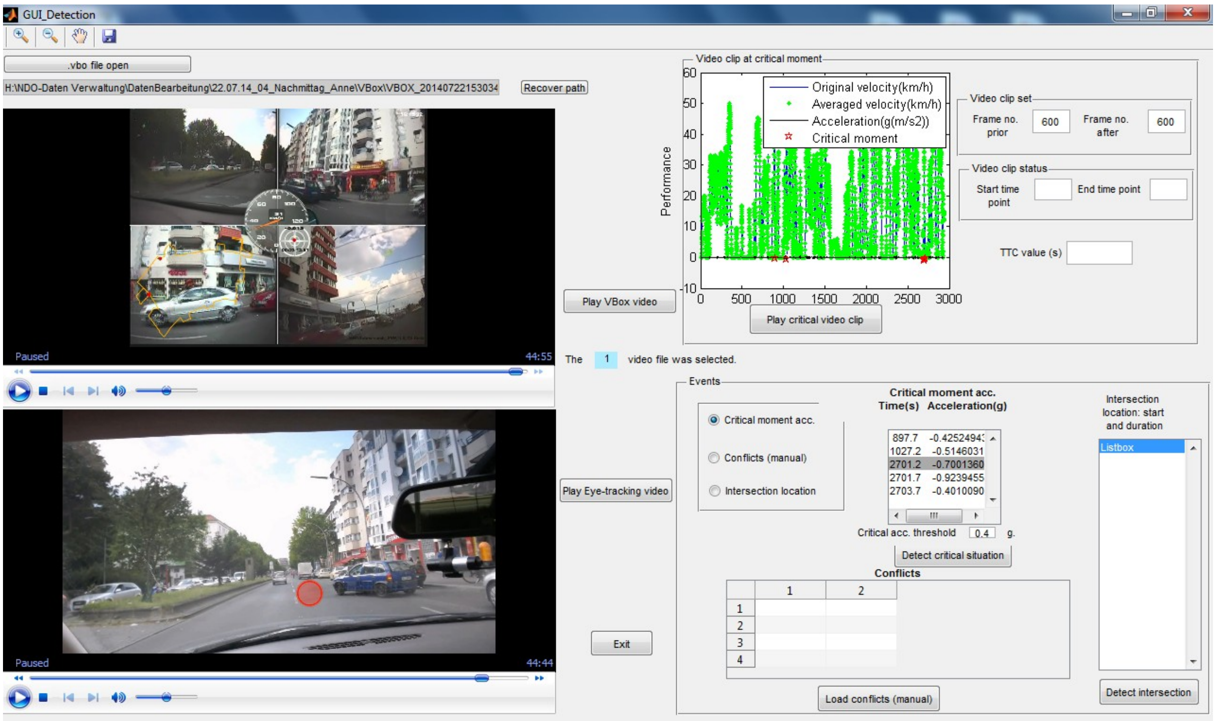


Figure 4-6 Graphical User Interface (GUI) for automated conflict detection and revision

Considering the existence of the frequent vibration and noises, the velocity data was firstly smoothed before it was used to detect safety-critical events, as shown in Figure 4-5. The average of five consecutive measured velocity values was regarded as one value in the smoothed velocity data. The sampling interval of velocity was 0.1 s, and therefore the interval of the smoothed velocity data was 0.5 s. The deceleration data that was used to detect safety-critical events was derived from the smoothed velocity data. This smoothing process could not only smooth the velocity/deceleration curve but also effectively eliminate the abnormal high deceleration/acceleration values caused by noises, as shown in Figure 4-5. The verification by data from six participants indicated that no real high decelerations/accelerations corresponding to critical situations were filtered out.

In event detection, a deceleration trigger of less than -0.4 g was used as the threshold. The kinematic trigger was set so low and simple as not to miss safety-critical events. Using this trigger, the possible safety-critical moments could be automatically detected, no matter who the involved parties were and where the events occurred. The events of interest in this study were concerned with cars and bicycles at signalized intersections. Thus, for each detected event, the video data and the dynamic data were revised in a time interval around the detected critical moments. Through this revision process, it could be determined if a detected event was a real safety-critical event rather than a high-deceleration-value-event caused by noises, and if it concerned a bicycle at signalized intersections. A Graphical User Interface (GUI) was programmed with Matlab (Release R2012b) to implement this detection and revision process, as shown in Figure 4-6.

This GUI program could load the recorded data of each individual participant. It could smooth the dynamic data, and detect and display the critical moments as well as the corresponding deceleration values. By clicking each critical moment, the VBox video data and eye-tracking video data could be synchronically played back around the detected critical moments. In this way, the researcher can easily learn what was happening inside and outside the car around the detected critical moments. While the dashboard simulator in the center of the VBox video frames displayed the real-time velocity change, the velocity curve could be also displayed in a separated window, so that it is observable how the velocity changed in the detected possible critical event. The eye-tracking video presented what the car driver looked at, providing information to what the drivers reacted.

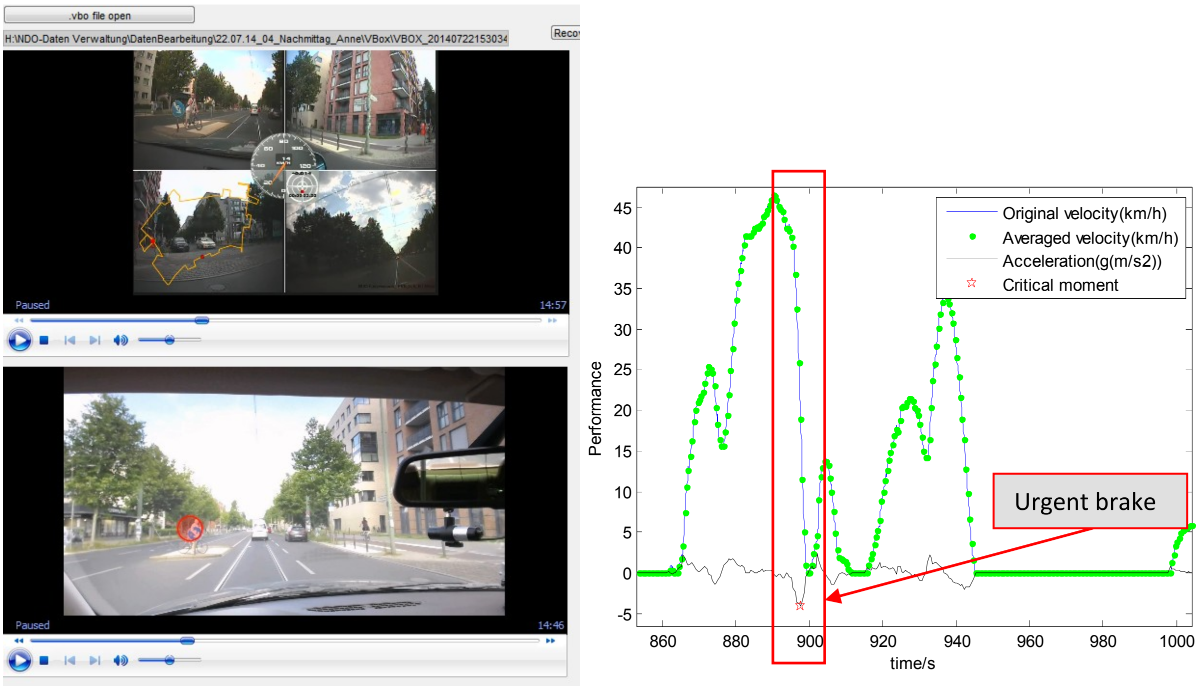


Figure 4-7 An example of detected events: Vbox video data (upper-left), eye tracking data (lower-left) and velocity/acceleration curve (right)

Figure 4-7 presents an example of a detected critical event. The driver met a bicycle waiting on a refuge island, ready to cross the road. As displayed in the video data, the driver did not detect the bicycle until he was very close to it. He conducted an urgent brake to give the right of way to the bicycle, as shown in the velocity-time curve. In this event, no noises were mixed in the data. It really concerned a high deceleration value. The car driver reacted (i.e. braked) to a bicycle. However, this event did not occur at a signalized intersection.

By processing the recorded data of twenty-two participants, twenty-seven safety-critical events (no crashes) were detected. The detailed information about these detected events was documented in Appendix 4.1. Nine events among them were caused by noises. The majority of the detected events took place in normal driving situations, where the car drivers should brake or decelerate according to the traffic law, but only exhibited high decelerations. For example, they braked or decelerated for turning, on red light or yielding to other road users at intersections. Only one detected event was related to a safety-critical situation, where the car driver had to brake to avoid a collision with a due-to-yield car from the right that did not follow the yield sign. Regarding the conflicting party and location, only one event involved a bicycle at signalized intersections. However, this event did not concern a safety-critical situation.

The reason why few conflicts of interest were detected in this way could be that road users usually move at slow speed at intersections, and therefore few high deceleration values could appear even at safety-critical moments. In the application of TCT, the severity of conflicts is determined not only by the amount of braking power required, but also by vehicle speed and distance to a conflict point and a friction coefficient [21]. Not all conflicts are accompanied with an extreme dynamical value. Thus, safety-critical event detection based on extreme dynamics could miss possible conflicts at intersections.

4.2.2.Manual conflict detection

In this section, manual video observation combining the dynamical data and visual behaviors of car drivers was carried out to extract possible conflicts between cars and bicycles at signalized intersections.

The manual conflict collection was accomplished by use of the professional video annotation tool ELAN, a free software developed by Max Planck Institutes for Psycholinguistics [189]. ELAN supported multi-video display. It could simultaneously display three video views from the three sets of data collection cameras, i.e. the VBox, eye tracking set and GoPro camera. Most of time, the observation of videos of the VBox and eye tracking headset was sufficient for conflict collection. The video of GoPro camera was only observed, when more information needed to be checked, such as the scene on the left side of the car and car drivers´ body movements. As described in section 4.1.3, the vehicular dynamics, including velocity and acceleration of the car, were integrated in the VBox video frames, and the gaze locations of car drivers were displayed in the video frame of the eye tracking set. Therefore, ELAN could combine the recorded videos, dynamics and visual behaviors in a single window for each detected event.

The three sets of data collection cameras were independent of each other. They were not started at the same time in data collection. To overcome this flaw, the recorded three video streams were first synchronized in ELAN for each participant before conflict collection. The VBox videos and GoPro videos were recorded with the constant frame rates of 25 fps and 60 fps, respectively. The original videos of the eye tracking headset were generated with a variant frame rate. However, the exported videos that contained the gaze location information were accurately adjustable in time by use of the timestamp information. The synchronization of three video streams was accomplished by lining up partial movements of objects commonly existing in the three videos, e.g. the pedestrian steps or the change of traffic signal phases.

For individual participant, the collected data at signalized intersections was played back and observed. All car-bicycle meeting events were detected. That is, bicycles that crossed an intersection were detected while the subject car was also crossing the intersection. By use of ELAN, a scheme with several variables was coded for each car-bicycle meeting event:

- Intersection number: in which intersection in the driving route the subject car met a bicycle or a group of bicycles;
- Movement directions of the subject car at intersections: the movement direction could be Rt (right-turning), Lt (left-turning) or Gt (going through));
- Movement directions of bicycles at intersections, indicated with the movement numbers, as shown in Figure 3-5;
- Bicycle numbers: A car-bicycle meeting event could be related to only one bicycle or a group of bicycles that moved in the same direction;
- If the event was a possible conflict. According to DOCTOR (Dutch Objective Conflict Technique for Operation and Research) method, a possible conflict, i.e. encounter, will be present, if at least one part needs to do something to avoid a collision. In other words, a possible conflict is a traffic situation in which two road users approach each other in time and space and may influence each other´s behaviors [190]. In data analysis, a possible conflict was determined, if the car driver had to react to the relevant bicycles. The reaction included braking, accelerating, swerving, keeping low speed to follow bicyclists and keeping still /delaying to start in order to give way to bicyclists. The reactions of car drivers to bicycles were mainly considered. Noticeable evasive actions by bicyclists were also considered indicators for possible conflicts.

Figure 4-8 shows the ELAN interface with an example of a detected car-bicycle meeting event. In this event, the subject car that turned right met a group of through bicycles in the red phase, and delayed to start to yield to the bicycles, after the traffic light turned green. It was a possible conflict, but was solved by the controlled behaviors of the car driver. Thus, it was not a safety-critical conflict.

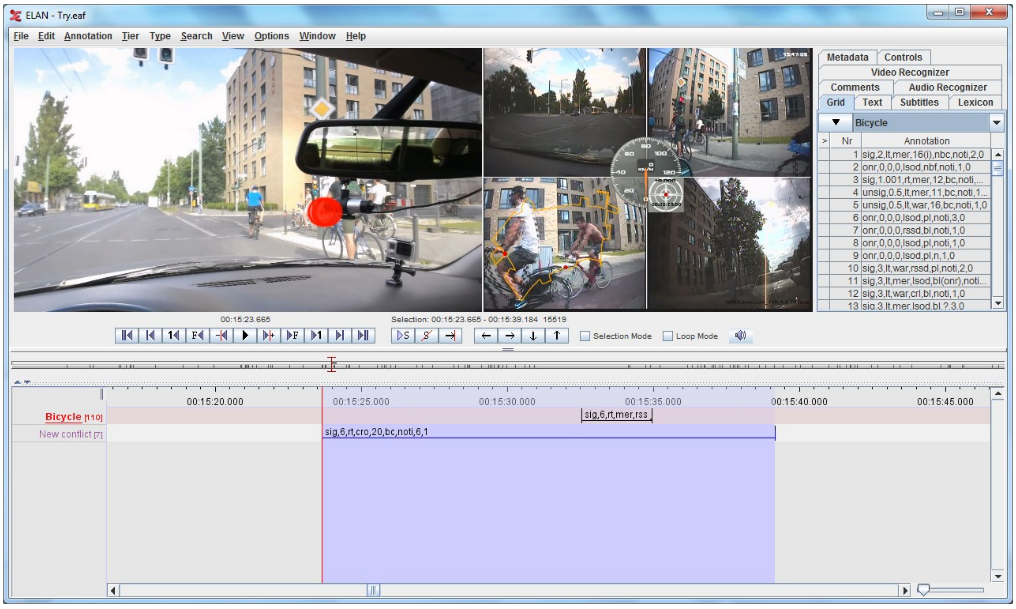


Figure 4-8 ELAN interface for the manual conflict detection

At signalized intersections, road users approaching from different directions ultimately have to share the same space. They could be separated in time under the control of traffic lights. However, most of time, they have to deal with each other, not supported by additional behavioral rules [190]. Therefore, possible conflicts frequently develop also at signalized intersections. From the collected data, 121 possible conflicts between the car and bicycles were detected. These possible conflicts were typed into car-bicycle scenarios as defined in section 3.3. Table 4-1 shows the numbers of detected possible conflicts corresponding to different scenarios. Considering that the numbers of movement directions (right turning, left turning and going through) in the preset driving route were different, the conflict numbers per movement type were calculated by dividing the number of possible conflicts by the corresponding movement numbers, and were shown in Table 4-1. The first three most frequent possible conflicts were R20, L12 and R17. This ranking was consistent with that of the accidents recorded in GIDAS, as shown in Table 3-2, and essentially with that of Berlin police-reported accidents, as shown in Table 3-1.

Table 4-1 Types and numbers of detected possible conflicts

Types	R20	L12	R17	R5	L10	L13	L14	L15	L16	L9	R16
No.	83	12	13	5	2	1	1	1	1	1	1
No. per movement	5.93	1.5	0.93	0.36	0.25	0.13	0.13	0.13	0.13	0.13	0.07

For each of the detected possible conflicts, gaze locations of car drivers were observed. Car drivers conducted direct scanning for bicycles or scanned the rear mirror or side mirror to detect bicycles during crossing intersections. In the majority of possible conflicts, car drivers could timely detect the presence of relevant bicycles, and timely react to avoid collisions with the bicycles. Car drivers, bicycles or both of them solved the most possible conflicts in a controlled manner.

Three events among these detected possible conflicts were involved in safety-critical situations, and they were conflicts. In the first conflict event, the car driver that intended to turn right did not detect the bicycle that was in parallel approaching the intersection behind the parked cars, until he entered the intersection. At the moment when the car driver first detected the presence of the bicycle, the car was moving at a relatively high speed. The car driver had to decelerate immediately to avoid collision with the bicycle. The second and third events concerned a similar situation. In approaching the intersection, the car driver that intended to turn right had scanned the intersection, driving at a relatively high speed because the right-turning route was clear; after the car entered the intersection, the driver detected a bicycle coming from the right road that intended to go through the intersection. The car had to brake immediately to avoid a collision. Figure 4-9 presents the situations of the three events at the moment when car drivers first detected the bicycles, i.e., first fixated on the bicycles.

The severities of the three conflicts were indicated by the Time to Accident (TA) measure. The TA is defined as the time that is remaining from when the evasive action is taken until the collision would have occurred if the road users have continued with unchanged speeds and directions [50]. The TA measure can be calculated by dividing distance to the potential point of collision by speed at the start point when the evasive action is taken. For the three conflicts, the start points were those when the car drivers first fixated on bicycles and meanwhile decelerated. Distance values were calculated by integrating the recorded velocity data based on time. Table 4-2 presents the severity measures of the three conflicts. In accordance with the "*uniform severity level*" and "*uniform severity zones*" based on the relationship between TA values and speed at start points, which was developed in the application of the Traffic Conflict Technique [50], the event 2 was a serious conflict approximately in severity level 1, while the other two events were non-serious events. In the three conflicts, only low deceleration values (less than 0.3 g) were involved.

Figure 4-9 Three detected safety-critical events, event 1, event 2 and event 3 (from top to bottom): Moments when car drivers first detected the presence of bicycles

Table 4-2 Severity measures of the three detected safety-critical conflicts

Safety-critical conflicts	Min. deceleration	Distance to conflict point (m)	Speed at start point (km/h)	TA (s)
Event 1	-2.53 g	14.29	23.84	2.16
Event 2	-2.32 g	5.04	9.86	1.84
Event 3	-1.15 g	11.92	18.49	2.32

4.3. Analysis of eye movements for events of R20

Motorists´ eye movements and visual attention are directly related to crash causality [230]. With improvements in eye-tracking technology, eye behaviors are contributing significantly to identifying the cause of crashes, as described in Chapter 2. Eye movement data can provide direct empirical evidence of potential hazards.

This section investigated the eye movements of car drivers in interactions with bicycles. This work was based on collected car-bicycle meeting events of R20, which is the most frequent car-bicycle conflicts/accidents at signalized intersections, indicated by both possible conflicts and accident data of Berlin Police and GIDAS. On the one hand, it was to demonstrate the bicycle-scanning strategies of car drivers in the scenario R20. On the other hand, it was to determine if car drivers´ visual attention on bicycles could be affected by changes in the traffic conditions.

4.3.1. Data analysis

The scenario R20 could occur in six different situations on a basis of the sequences of the car´s and the bicycle´s arriving at intersections and the traffic light phases, as shown in Figure 4-10. In the situation R20_1, the car is in the period of approaching the intersection, while the bicycle has entered the intersection and is crossing the intersection in the green phase. In R20_2, the car is approaching the intersection, while the bicycle is waiting at a red light. In R20_3, the car and the bicycle are approaching the intersection at the same time, when the traffic light is green. In R20_4, the car and the bicycle are approaching the intersection at the same time, but they have to stop at a red light. In R20_5, the car is already at the intersection and waiting at a red light, while the bicycle is approaching. In R20_6, the motorist is ready for turning or is executing right-turning at a green light, while the bicyclist is approaching the intersection. In different R20 situations, the visibility of bicycles is different for motorists, and therefore the bicycle-scanning strategies of motorists are different.

During a right-turning process, a car driver could generally go through three periods, namely approaching the intersection, waiting at red and turning. The period of turning started from the point when the car entered the intersection and ended when the car driver completed the turning. Car drivers might allocate visual attention to the relevant bicycles in any period. They might fixate directly on bicycles ahead of the car, while they might conduct shoulder check or fixate on interior or external rear view mirrors to observe bicycles approaching from behind. The bicycle-scanning strategies were reflected how car drivers allocated their visual attention to bicycle in different periods as well as by shoulder checks and mirror checks.

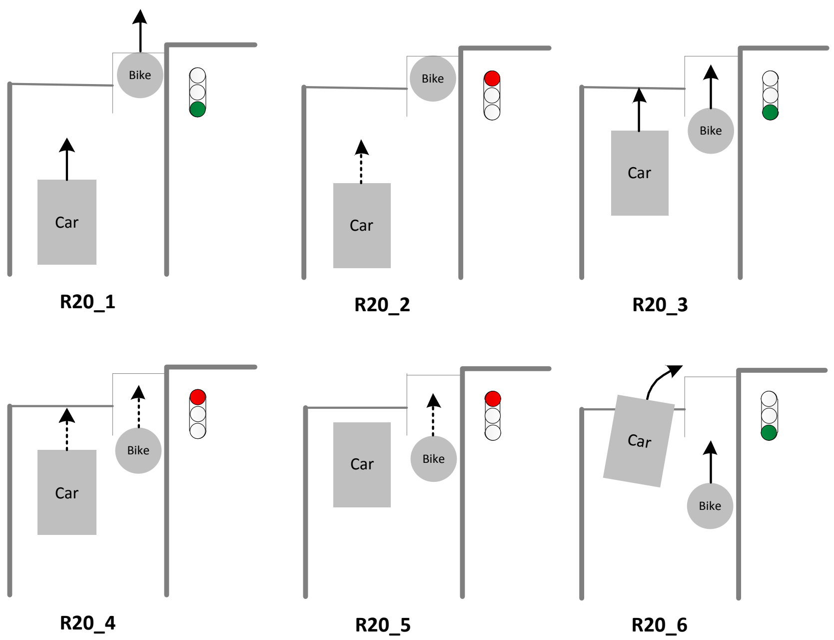


Figure 4-10 Six situations of R20 scenario on a basis of the sequences of the car´s and the bicycle´s arriving at intersections and the respective traffic light phases

Visual attention of car drivers was measured by fixations. When the gaze was located on a bicycle or a group of bicycles in more than six consecutive frames (a frame corresponded to about 0.03 seconds), it was regarded as a fixation on bicycles. The duration of a fixation was measured and recorded by the number of frames in which the gaze was located on bicycles.

The information collection about bicycle-scanning of car drivers was accomplished by ELAN. The analyzed car-bicycle meeting events of R20 were those collected in 4.2.2. They were coded with the following variables:

- R20 situations, as shown in Figure 4-10;
- If it was a possible conflict (1) or not (0);
- Bicycle number;
- Presence of oncoming bicycles right (i.e. in motion 17, as shown in Figure 3-5): yes (1) or no (0);
- Presence of right-turning bicycles (i.e. in motion 5, as shown in Figure 3-5) : yes (1) or no (0);
- Presence of conflicting pedestrians in the crosswalk : yes (1) or no (0);
- Presence of cars ahead of the subject car: yes (1) or no (0);
- Numbers and durations of fixations on bicycles in the period of approaching;
- Numbers and durations of fixations on bicycles in the period of waiting at red;
- Numbers and durations of fixations on bicycles in the period of turning;
- Numbers and durations of fixations on bicycles by shoulder checks;
- Numbers and durations of fixations on bicycles by mirror checks.

4.3.2. Analysis results

Bicycle-scanning strategies

From the recorded data, 146 events of R20 were collected. For each event, the average fixation duration on per bicycle was documented in each period. The average duration was documented as well for fixations on bicycles that were made by shoulder checks and mirror checks. This information could provide a measure of bicycle-scanning strategies of car drivers.

Through fixations on bicycles, car drivers can complete two tasks. One task is to detect the existence of bicycles, i.e. fixation for detection. It usually refers to car drivers´ first fixation on bicycles. Another task is to observe the speed and relative location of bicycles to make appropriate decisions combining the surrounding traffic conditions, i.e. fixation for observation. A safe right-turning requires car drivers to complete at least the two independent tasks.

Bicycle-scanning strategies were analyzed in different R20 situations and presented in box plots by use of SPSS. Figure 4-11 shows the bicycle-scanning strategy of car drivers in the scenario R20_1. In all events except the event outlier 1, fixations on bicycles only occurred in the period of approaching. In this situation, the task of fixation for detection could be easily completed, since bicycles were clearly presented in the forward field of view of car drivers. As described above, in events of R20_1, bicycles were crossing intersections, when the car was approaching intersections. In most cases, bicycles had crossed the intersection, when the car entered the intersection and started turning. Normally, car drivers did not have to take evasive actions to avoid crash with bicycles. Fourteen events of R20_1 were collected, only one of them involved in a possible conflict. Events of R20_1 were not likely to lead to a safety-critical situation or a crash.

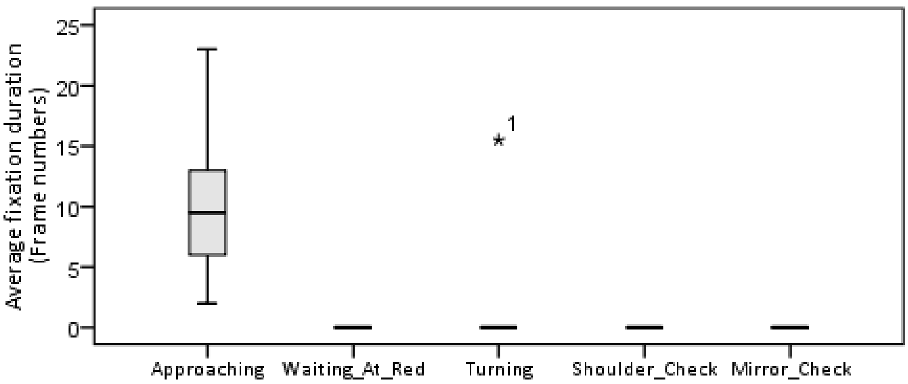


Figure 4-11 Bicycle-scanning strategy in R20_1

Figure 4-12 shows the bicycle-scanning strategies of car drivers in situations R20_2, R20_4 and R20_5. A number of thirteen events of R20-2, nine events of R20-4 und thirty-five events of R20_5 were collected. In the three situations, no matter which party first arrived at intersections (the car or bicycles), they would go through a period, in which car drivers kept still and were charged with few driving tasks, and therefore had enough visual attention to scan bicycles, which were also not moving. In addition, due to the installation of the advanced bicycle-stop lines, car drivers could easily detect bicycles. Thus, in the three situations, the most fixations on bicycles occurred in the period of waiting-at-red. After the light turned green, car drivers had to yield to bicycles and fixate on bicycles to find the right time to cross. Therefore, a number of fixations on bicycles occurred in the period of turning. For R20_2 and R20_4, bicycles were already at intersections or approaching intersections, when the car was approaching. As a result, some fixations also occurred in the approaching period in R20_2 and R20_4. In the events of the three R20 situations, bicycles could be easily detected, and the interactions between car drivers and bicyclists were easily handled. For example, car drivers who started from a (shortly) stationary position only needed to yield to cyclists who were easily detectable. Events in these R20 situations hardly developed into safety-critical situations or crashes.

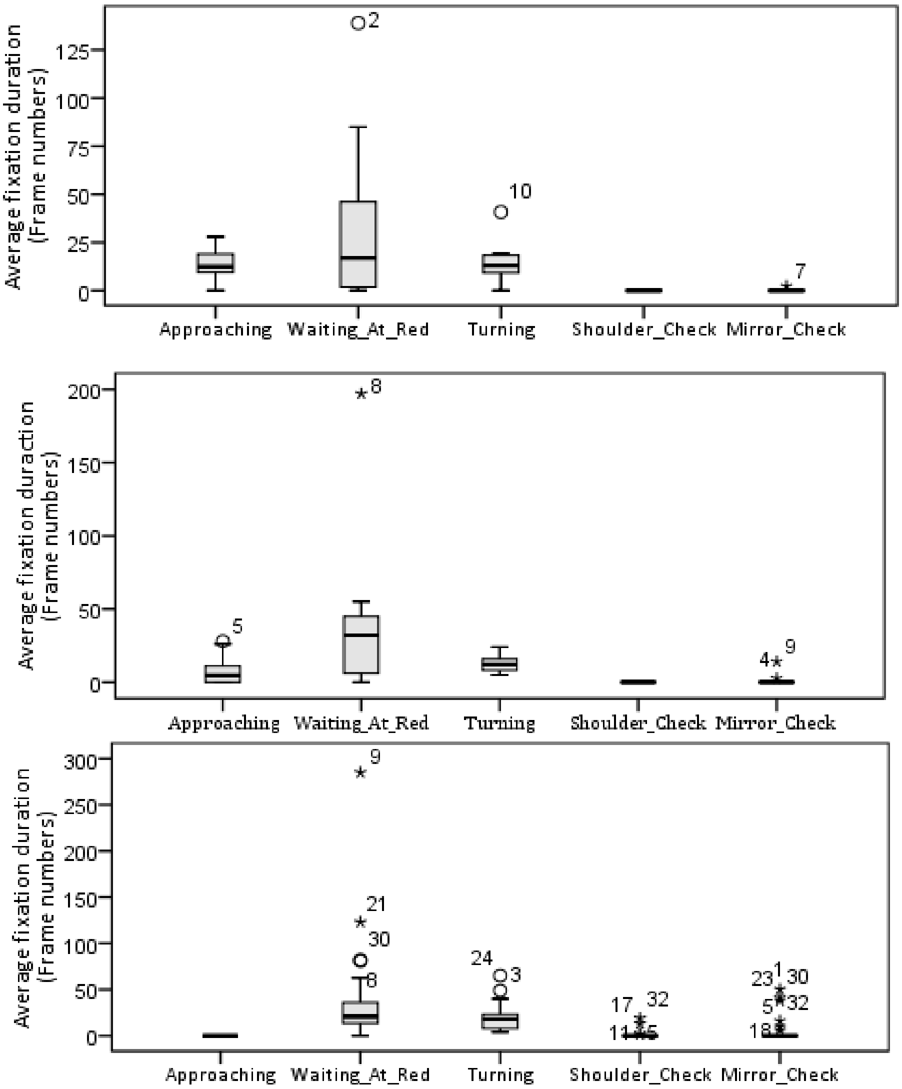


Figure 4-12 Bicycle-scanning strategies in R20_2 (top), R20_4 (middle) and R20_5 (bottom)

In the situation R20_3, when the traffic light is green, bicycles are approaching the intersection at the same time as the car. There were two sub-situations for R20_3. In sub-situation 1, cyclists rode always in the forward view of car drivers. In sub-situation 2, the car overtook bicycles in approaching and arrived at the intersection prior to bicycles. Figure 4-13 shows the bicycle-scanning strategies of car drivers in the two sub-situations. In sub-situation 1, fixations on bicycles occurred only in approaching and turning periods. In this sub-situation, it was important that bicycles could be detected in the approaching period. If car drivers had not detected the bicycles until the turning period, the car would have entered the intersection at a relatively high speed (, since the car driver most probably perceived that the intersection was clear). In this case, the situation could easily result in conflicts or even crashes.

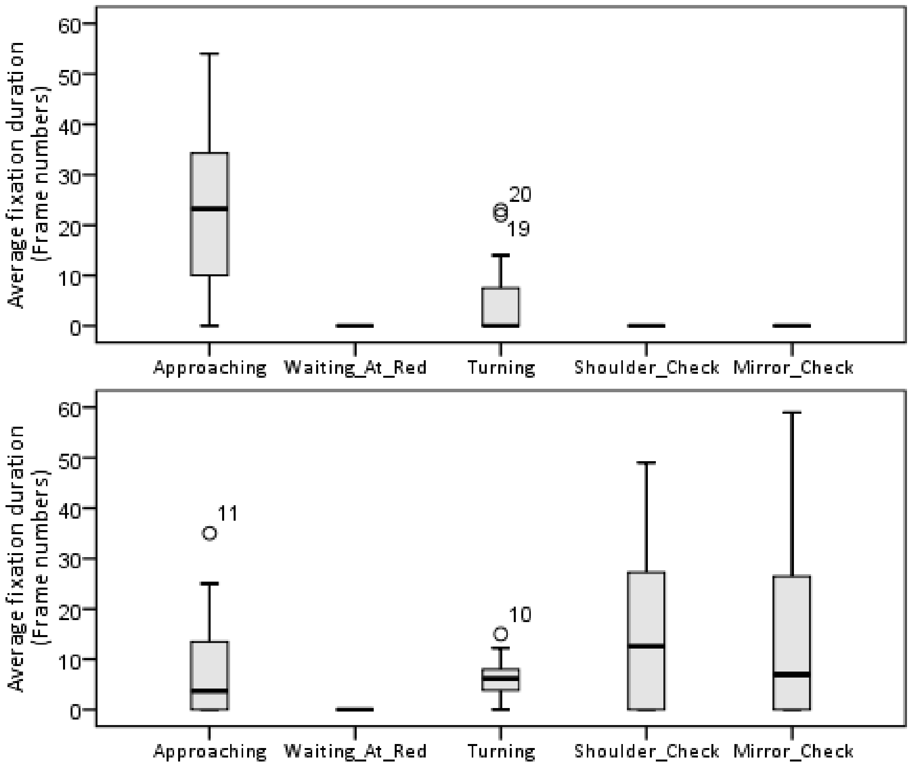


Figure 4-13 Bicycle-scanning strategies in R20_3: Sub-situation 1 (Top) and Sub-situation 2 (Bottom)

In sub-situation 2 of R20_3, apart from periods of approaching and turning, car drivers conducted fixations on bicycles mainly by shoulder checks or mirror checks. The shoulder checks or mirror checks were executed to scan the bicycles that car drivers had passed by in the approaching period. Car drivers could have detected these bicycles during the approaching period. If yes, shoulder or mirror checks were explicitly made to observe the bicycles; if no, shoulder or mirror checks were made to both detect and observe the bicycles. Whatever the case was, it has to be emphasized that it is important to perform shoulder or mirror checks for a safe right turning in this sub-situation.

The situation R20_3 corresponded to the most frequent events of R20. Forty-eight events of R20_3 were collected. Compared with the other scenarios, namely R20_1, R20_2, R20_4 and R20_5, road users involved in the situation R20_3 are more likely to be involved in safety-critical situations or crashes, especially if bicycles are undetected by car drivers in approaching period (in the sub-situation 1) or if no shoulder or mirror checked are carried out by car drivers before turning (in the sub-situation 2). The risk in the scenario R20-3 could be mitigated through appropriate installation and improvements of bicycle facilities at intersections (in the sub-situation 1) and in the form of advanced road user education (in the sub-situation 2).

In situation R20_6, the car is ready for right-turning or is turning at a certain amount of speed, when bicycles are approaching the intersection. The bicycles have the right of way. The car driver should detect the bicycles before turning, or else safety-critical events would occur. In this situation, the shoulder or mirror checks are of great importance. As shown in Figure 4-14, the fixations on bicycles were mainly performed by shoulder and mirror checks. Through these fixations, car drivers detected the bicycles. Like the situation R20_3, this situation is also of high risk, and road user education (i.e. performance of shoulder and mirror check) might effectively mitigate crashes.

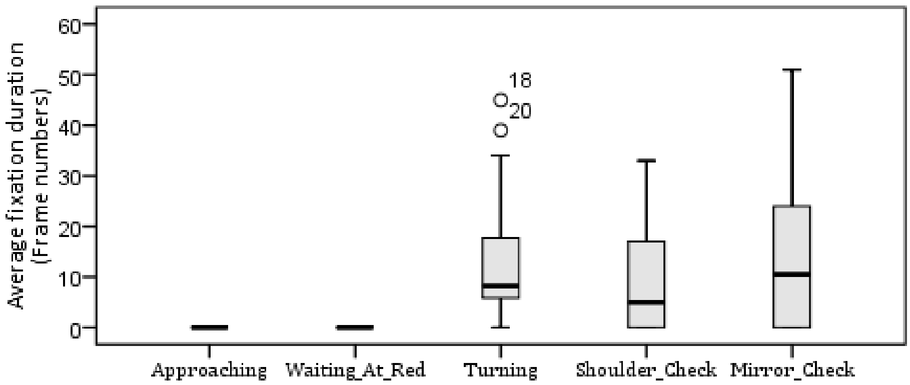


Figure 4-14 Bicycle-scanning strategy in R20_6

In these plot boxes, some outliers are observable, which are marked with circles or asterisks. They are abnormal values corresponding to special situations. The events that each outlier corresponded to were observed concerning the detailed situations, and stated in Appendix 4.2.

Effects of traffic conditions

In addition to the distribution of fixations on bicycles in different right-turning periods in the scenario R20, the changes of car drivers´ visual attention to bicycles was also studied in response to the changes of traffic conditions. In the scenario R20, car drivers might have to handle relationships with other road users besides the through bicycles, and allocate the limited visual attention to other road users. In other words, the other road users would compete with the through bicycles over the visual attention. These road users might be on-coming bicycles in motion 17 (as shown in Figure 3-5), right-turning bicycles in motion 5 (as shown in Figure 3-5), pedestrians in conflicting crosswalks and other motorized vehicles ahead of the subject car. Therefore, it was hypothesized that the presence of other road users might influence car drivers´ visual attention to the through bicycles.

The mean total fixation duration on bicycles was used as the dependent variable to measure car drivers´ visual attention, i.e. the total fixation duration on per through-bicycle during a right-turning process. This variable excluded the fixations in waiting-at-red periods. The reason was that the majority of fixations in this period were invalid, and greatly depended on the duration of the red phases.

The database of the mean total fixation duration on bicycles in each event was divided into two groups, according to five independent variables respectively. These independent variables were the presence of oncoming bicycles in motion 17 and not, presence of right-turning bicycles in motion 5 and not, presence of pedestrians in conflicting crosswalks and not, presence of cars ahead and not, and if the event was a possible conflict and not. Table 4-3 presents the event numbers in each group. The dependent variable was not normally distributed for any of these groups, indicated by a Kolmogorov-Smirnov test, which is a commonly used test for normality. Thus, the Mann-Whitney U test, which is a common non-parametric test for comparison between two independent groups, was carried out to determine if there was any difference in the mean total fixation duration on bicycles with respect to these five independent variables, respectively.

Table 4-3 Mann-Whitney U test of the mean total fixation duration on bicycles with respect to independent variables

Independent variables	No. of events in each group		Mann-Whitney U Test: Mean Total Fixation Duration on Bicycles			
	0 (No)	1 (Yes)	Mean Rank 0	Mean Rank 1	p-value	Significant
If possible conflict	46	100	50.13	**84.25**	**<0.001**	**Yes**
Presence of oncoming bicycles in motion 17	121	25	72.07	80.42	0.369	No
Presence of right-turning bicycles in motion 5	95	51	70.03	79.96	0.176	No
Presence of pedestrians in conflicting crosswalks	63	83	67.21	78.27	0.118	No
Presence of cars ahead	102	44	73.03	74.58	0.839	No

Table 4-3 presents the results of the Mann-Whitney U test. The statistical significant difference was found in the mean total fixation duration on bicycles between groups that were divided depending on the variable if an event was a possible conflict or not. This result indicated that the car drivers spent more time fixating on the through-bicycles, if he/she had to react to the through-bicycles to avoid collisions in an event. No statistical significant changes were identified in the mean total fixation duration on the through-bicycles in presence of oncoming bicycles in motion 17, right-turning bicycles in motion 5, pedestrians in conflicting crosswalks or cars ahead. Although fixations were made on the other road users in these events, it did not decrease the mean total fixation on the through-bicycles. The result does not support the hypothesis.

4.4. Conclusion and discussion

The method of NDO is proved reliable and efficient to address traffic safety. Despite considerable NDO studies, few have investigated interactions between car drivers and bicyclists. Several NCO studies that focused on interactions between car drivers and bicyclists, however, were conducted from perspective of bicyclists. This chapter carried out a Quasi-NDO study to investigate interactions between car drivers and bicyclists at signalized intersections from perspective of car drivers, who are responsible for more car-bicycle accidents at signalized intersections than bicyclists are.

Participants were recruited to drive a car instrumented with a Video Vbox and a camera. They were requested to wear an eye tracking headset in driving the car in real traffic. Drivers´ driving behaviors, including car-operation behaviors, body movements and eye movements, and the driving environment were recorded.

From the collected data, car-bicycle conflicts were detected and identified. By use of the automated conflict detection based on a deceleration trigger, only one car-bicycle conflict at signalized intersection was identified. Nevertheless, this conflict did not concern a safety-critical situation. In contrast, the manual conflict detection through video observation combining the dynamical data and eye movement data extracted up to 121 possible conflicts, in which car drivers needed to do something to avoid a collision with bicycles. Most possible conflicts were solved in a controlled manner. Three events among them were involved in safety-critical situations. The three events reveal two potential risky situations between cars and bicycles at signalized intersections: the first situation concerns a right-turning car and a through-bicycle behind parked cars; the second situation concerns a right-turning car and a bicycle coming from the right road.

The identified possible conflicts were typed into car-bicycle scenarios. The first three most frequent possible conflict scenarios were essentially consistent with that indicated by the GIDAS data and Berlin Police-reported accident database. Both conflicts and accidents show that the most frequent scenario is R20, in which the car turns right and the bicycle goes through the intersection. Considering the eye movement data can provide safety-related evidence about visual attention, the collected eye movement data was analyzed for the scenario of R20. The analysis gave insight into how car drivers visually interact with bicycles.

Based on 146 collected events of R20, bicycle-scanning strategies of car drivers were analyzed. The strategy involved the amount of bicycle-fixation time in three periods of a car´s right-turning process, namely approaching the intersection, waiting at red and turning, as well as duration of fixations made by shoulder checks and mirror checks. R20 scenarios were categorized into six situations on a basis of sequences of the car´s and the bicycle´s arriving at intersections and the traffic light phases. The strategies showed that in four of six R20 situations, car drivers could easily detect bicycles, and the interactions between car drivers and bicyclists were easily handled. Events in these R20 situations hardly developed into safety-critical situations or crashes. Events in the other two R20 situations could be more likely to result in conflicts or even crashes. The bicycle-scanning strategies indicated that the risk in the two situations could be mitigated through appropriate installation and improvements of bicycle facilities at intersections and in the form of advanced road user education (i.e. performance of shoulder and mirror check).

Another analysis regarding eye movements focused on car drivers´ mean fixation durations on per through bicycle in the scenario R20. The result indicated that the car drivers spent more time fixating on the through-bicycles, if they had to react to the through-bicycles to avoid collisions in an event. However, mean fixation durations were not influenced by the presence of other related road users, such as presence of oncoming bicycles, right-turning bicycles, pedestrians in conflicting crosswalks and cars ahead.

The work in this chapter reveals potential risky situations between cars and bicycles at signalized intersections, with detailed information on the chain of events by conflict detection. This is one of the main findings in this work. Concerning conflict detection method, automated conflict detection based on a deceleration trigger could miss conflicts, because not all conflicts are accompanied with extreme values. In contrast, manual conflict detection could effectively identify conflicts through video observation combining the eye movement data and dynamical data. The eye movement data facilitated the conflict detection/identification process, since it could supply information e.g. to whom and why the car drivers reacted. Normally, manual video observation is very time-consuming. However, the related data at signalized intersections could be easily positioned according to the geographical data. This could save a great amount of time. In addition, the analysis of the eye movement data implies measures to decrease the risk in R20 scenarios and reveals influence factors on bicycle-fixation durations of car drivers. This is the second important finding in the work.

Nevertheless, the data collection time was very short, and therefore only two risky situations were detected. Moreover, due to the limited number of participants, the conclusions on eye movements need to be confirmed. A larger-scale study with longer data collection time and more participants is expected in the future work. The created framework could be used for such a study, but some improvements could be done:

- The applied eye-tracking headset is sensitive to its position change relative to the eye. A slight change could generate errors in gaze location data. In the long-time data collection, even the mimics could easily change the relative position. An updated version of this eye-tracking headset or a new type of eye-tracking headset needs to be achieved for a larger-scale study.
- The digital map with signalized intersection locations for areas in which the participants will drive should be available, so that the related driving information at intersection could be easily positioned for manual conflict detection. This could make the conflict detection semi-automated.
- In this study, participants´ own cars could be instrumented and participants could decide where and when to drive, making the collected data more natural.

5. Risk perception for car-bicycle scenarios at signalized intersections

Risk perception is believed to be a crucial indicator for human behaviors. It is an important contribution factor for traffic safety. The links between perceived risk and risk-taking behavior and between perceived risk and objective risk are well established. Generally, the less one perceives risk in a given situation, the more likely he or she is to adopt risky behaviors [191] and the more likely he or she is to be involved in crashes [192]. With regard to car-bicycle safety at signalized intersections, a study on risk perception of road users would tell whether car drivers and cyclists perceive risk accurately or in the same range in interaction with each other. This topic is interesting, because any discrepancy between perceived and objective risk could play a role in crash occurrence. Such a study could help in determining what to do to make perception more accurate and therefore avoid crashes and fatalities.

In this chapter, car drivers´ and cyclists´ risk perception is investigated for common car-bicycle accident scenarios at signalized intersections by an online survey. There are four major aims. The first is to investigate risk perception of car drivers in the common car-bicycle accident scenarios. The second is to explore how cyclists perceive risk in these scenarios. The third is to compare perceived risk and objective risk, as to find out whether discrepancy exits between perceived risk and objective risk. The last is to compare perceived risk of the two road user types, in order to find out whether there is difference in perceived risk between cyclists and car drivers.

The questionnaire design, data collection and part of data analysis in this chapter were carried out with the help of a bachelor. This bachelor thesis work was supervised by the writer of this dissertation, as presented in the bachelor thesis [193].

5.1. Determination of car-bicycle scenarios to be evaluated

Accident scenarios could be described based on the geometrical configuration, namely on the motion directions of cars and bicycles, and their relative locations, as described in section 3.3. However, not all the scenarios were to be evaluated in this work. In determining accident scenario to be evaluated, three factors were considered:

- The first factor was common motions at intersections. Only those accident scenarios were selected, which concern common motions at intersections, including through-going, right-turning and left-turning. Therefore, accident scenarios concerning vehicles that park, back up and turn over were excluded.
- The second factor was bicycles that go through intersections in the wrong direction. Accident scenarios involving a bicycle that goes through intersections in the wrong direction were included, since bicycles often move in a more flexible way.
- The third factor was red-light violation. Accident scenarios related to red-light violation were excluded, since red-light violation is obviously a type of highly dangerous behaviors.

In accordance with the three factors, seventeen accident scenarios were selected, as illustrated in Figure 5-1.

These scenarios are denoted with a letter, namely R (Right-turning of car), L (Left-turning of car) or G (Going-through of car), and numbers, the same as described in section 3.3.

Accident frequencies of the determined scenarios has been obtained in Chapter 3, based on accident data reported in Berlin over eleven years (from 2003 to 2013). For reading comfort, the analysis result is listed again in Table 5-1. The accident frequencies were used to measure objective risk of these scenarios.

In addition, traffic volume data was analyzed at 209 signalized intersections. The database was provided by the Senate Department for Urban Development and the Environment (Berlin). The analysis shows that approximately 10 times as many cars as bicycles cross signalized intersections in Berlin. It suggests that cyclists have a higher exposure rate to car-bicycle accidents at signalized intersections. In other words, objective risk at intersections is higher for bicycles than for cars.

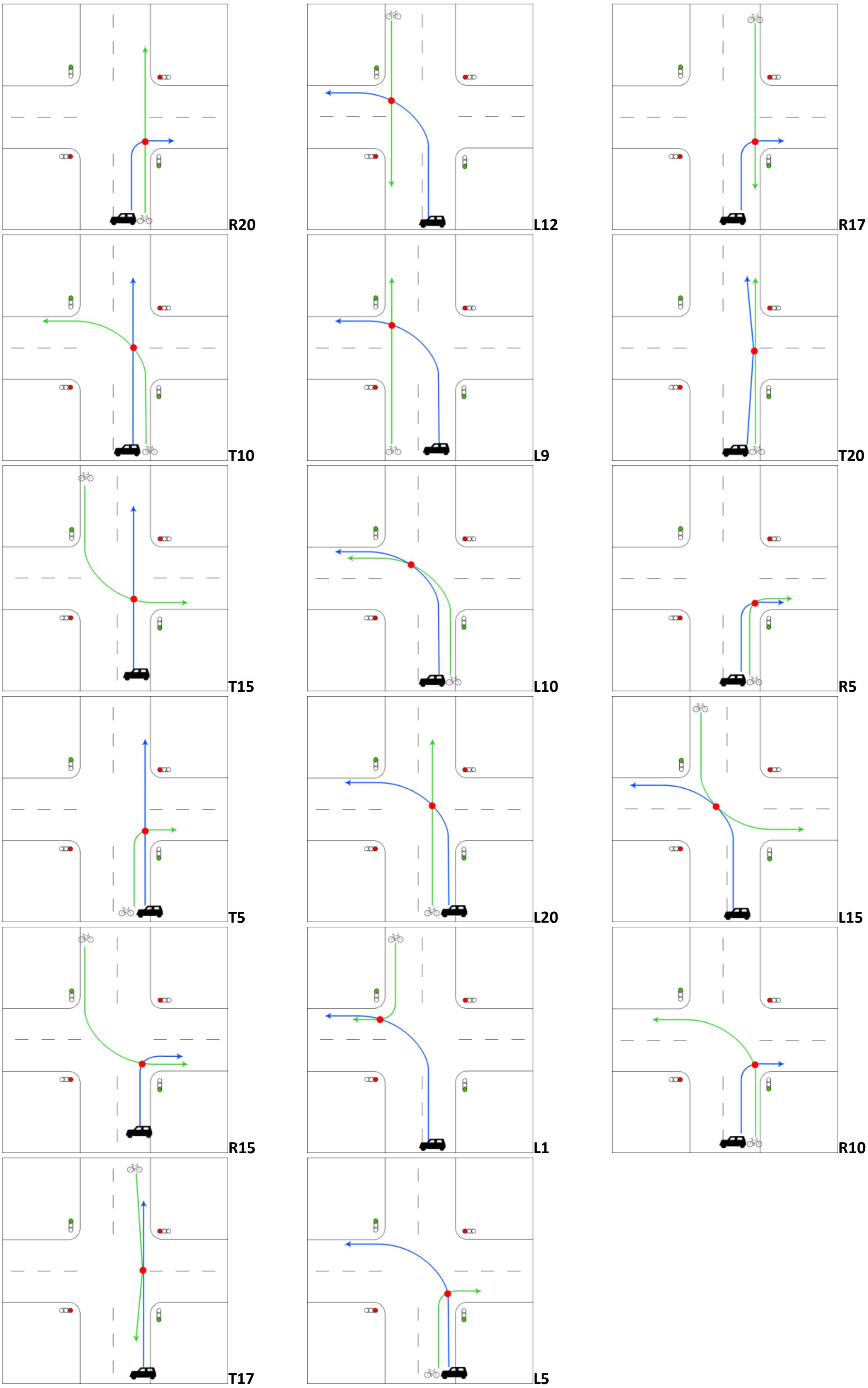


Figure 5-1 Diagrams of common accident scenarios. Arrows indicate motion directions of cars and bicycles [193]

5.2. Method: online survey

5.2.1. Sampling and administration

An online survey was conducted to gather information on risk perception of road traffic participants in Berlin. The survey was submitted via the internet to reach specific groups associated with Berlin residents. These groups included "Berlin", "TU Berlin", "AutomarktBerlin", "ADFC Berlin (a bicycle club)" and Facebook friendship circles of the researchers. The members of these groups were invited to participate in this survey without financial incentives. This survey was active for a three-month period (November 2014 -January 2015).

5.2.2. Questionnaire design

A custom-designed web-based program was employed to design the questionnaire, and to save and manage the collected data. A pilot survey was carried out before the data collection, to examine clarity and face validity of the questionnaire. It was established that it took approximately 15 minutes to complete this questionnaire.

The questionnaire comprised three parts. The first part was a short description about the survey background (a scientific study with the theme "accident scenarios between cars and bicycles at signalized intersections"), the objective (the respondents´ individual opinion is expected), the structure and the time requirement. The second part was related to the frequently used transport mode of the respondents. In accordance with the answers, the respondents were categorized into car drivers who have most frequently used passenger cars, bicyclists who have most frequently used bicycles and others, which included pedestrians and road users who have most frequently used the public transport.

The third part was the main component of this questionnaire. In this part, the seventeen selected accident scenarios were illustrated by use of diagrams and text descriptions, as shown in Figure 5-2. The scenario diagrams were prepared in two versions, one for cyclists and one for car drivers, so that the road user type of respondents always came from the bottom approach in the diagram. This was aimed at making respondents to imagine better themselves in the given scenarios. Respondents were required to score these scenarios according to the frequencies of the accident scenarios. As a widely used measure of opinions with a great degree of munance, a five-point Likert scale was used to answer this question. The scales range from 1= never to 5= very frequently. These scored scales indicated their perceived risk for these scenarios (no matter the consequence of accidents). Figure 5-2 presents one example scenario (R32), showing how this part was structured.

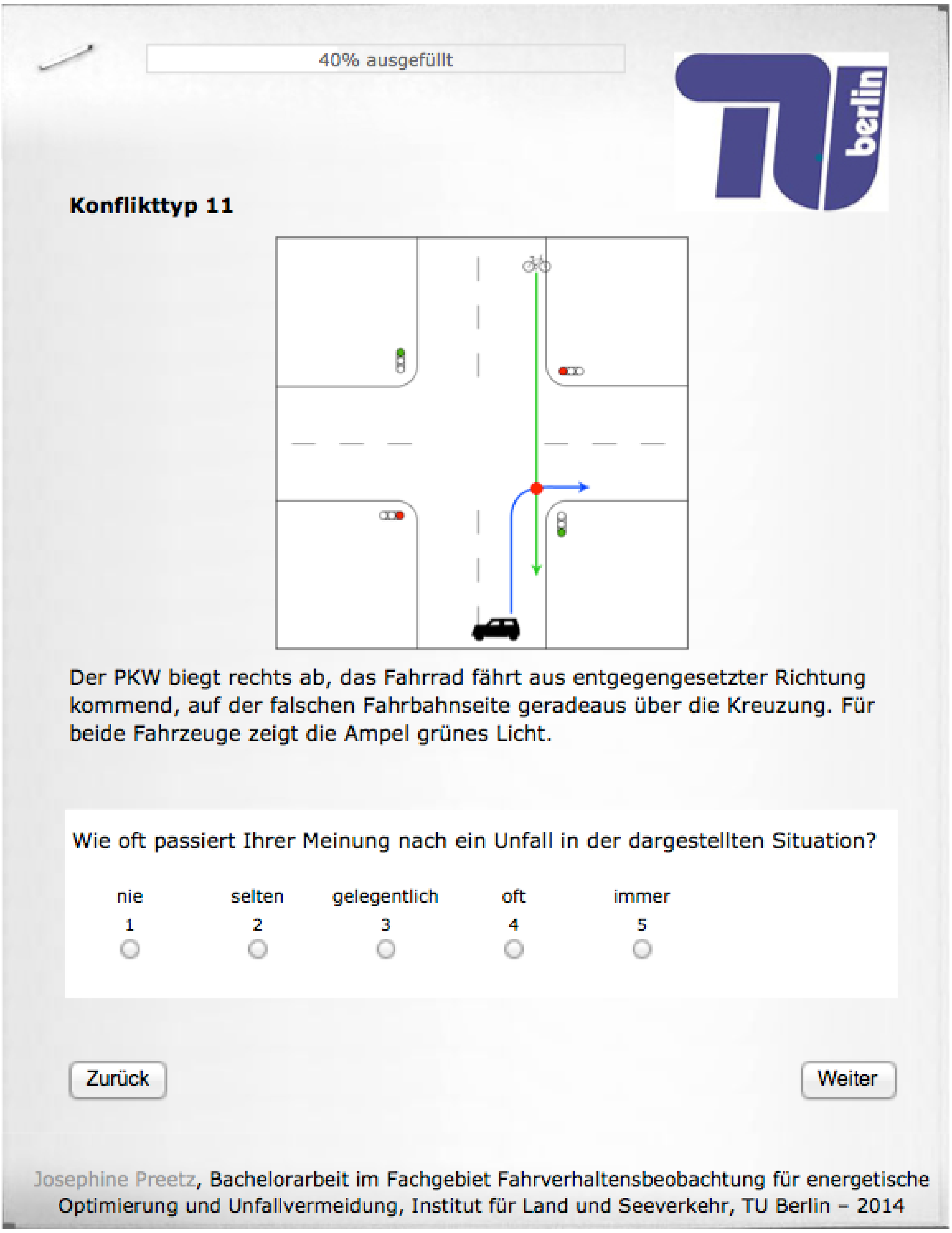


Figure 5-2 An example scenario (R32) in the third part of the questionnaire, for assessing perceived risk (version for car drivers) [193]

5.2.3. Sample characteristics

1,656 respondents have clicked the online questionnaire, and 603 of them have finished the survey. The data records were filtered out, when the respondents have completed the survey in a very short time or given the same score to all scenarios. Valid data records were finally obtained from 525 respondents. Categorizing the respondents in accordance with the most frequently used transport modes, the 525 respondents consisted of 209 car drivers, 197 cyclists and 119 "other road users". Data records from "other road users" were excluded from data analysis, since they are not the direct participants in cycling and car driving.

5.3. Data analysis

Scales that the respondents have used to rate the frequencies of accident scenarios were used to indicate their risk perception. A higher score on the scales indicates higher perceived risk. Cronbach´s alpha coefficient was applied to evaluate the internal consistency of the risk perception scales. Cronbach´s alpha coefficients were 0.75 for the cyclist sample, 0.78 for the car driver sample and 0.76 for the whole sample. It indicates that the reliability of risk perception is acceptable. To get an overview of the collected data, the frequencies of scales for perceived risk by the whole sample were counted for each scenario. The result is presented in Figure 5-3.

The means and standard deviations (S.D.) of perceived risk scales were calculated for the car driver sample, the cyclist sample and the whole sample. The Kolmogorov-Smirnov test, which is a commonly used test for assessment of normality, indicated that scales for all scenarios did not follow a normal distribution (all $p < 0.001$). Thus, the data analysis of risk scales was carried out by use of non-parametric tests.

As stated previously, the means of perceived risk scales were used to measure the subjective risk of each scenario, while accident frequencies were used to measure the objective risk. The scenarios were ranked based on the means of risk perception scales (subjective ranking) and the accident frequencies (objective ranking). The ranking results are presented in Table 5-1. The subjective ranking and the objective ranking were compared by use of Spearman´s test, which is a common non-parametric measure of association between two ordinal variables. When regarding the accident frequency of each scenario (see Table 5-1), accident frequency differences are not distinct between some adjacent scenarios. Therefore, paired-sample t-test was carried out for accident distributions in years (from 2003 to 2013) for each two adjacent scenarios (, since the accident frequency for each scenario is normally distributed in years). Significant differences were found between:

- the first and second scenarios (cut-off point 1, mean difference=146, $p<0.001$),
- the second and third (cut-off point 2, mean difference=104, $p<0.001$),
- the third and fourth (cut-off point 3, mean difference=55, $p<0.001$),
- the fifth and sixth (cut-off point 4, mean difference=5, $p<0.005$),
- the seventh and eighth (cut-off point 5, mean difference = 8, $p<0.005$)
- and the eighth and ninth (cut-off point 6, mean difference = 5, $p<0.005$).

The scenarios were categorized into seven classes in terms of objective risk at the six cut-off points. The classification result is also presented in Table 5-1 (see the item "Objective risk class").

In order to explore the differences of risk perception between car drivers and cyclists, the means of perceived risk scales, as shown in Table 5-1, were first compared. In addition, Mann-Whitney U test, which is a commonly used non-parametric test for comparison between two independent groups, was used to compare the perceived risk scales of car drivers and cyclists for each scenario.

5.4. Data analysis results and discussion

5.4.1. General results

Figure 5-3 presents the perceived risk of the whole sample for each scenario. Scales 1-5 rate the perceived risk. A higher scale indicates the higher perceived risk. Looking at the perceived risk scales for all scenarios, the scales 4 (an accident often happens) and 2 (an accident occasionally happens) were most frequently chosen. The extreme scales 1 (an accident never happens) and 5 (an accident very frequently happens) were least frequently chosen.

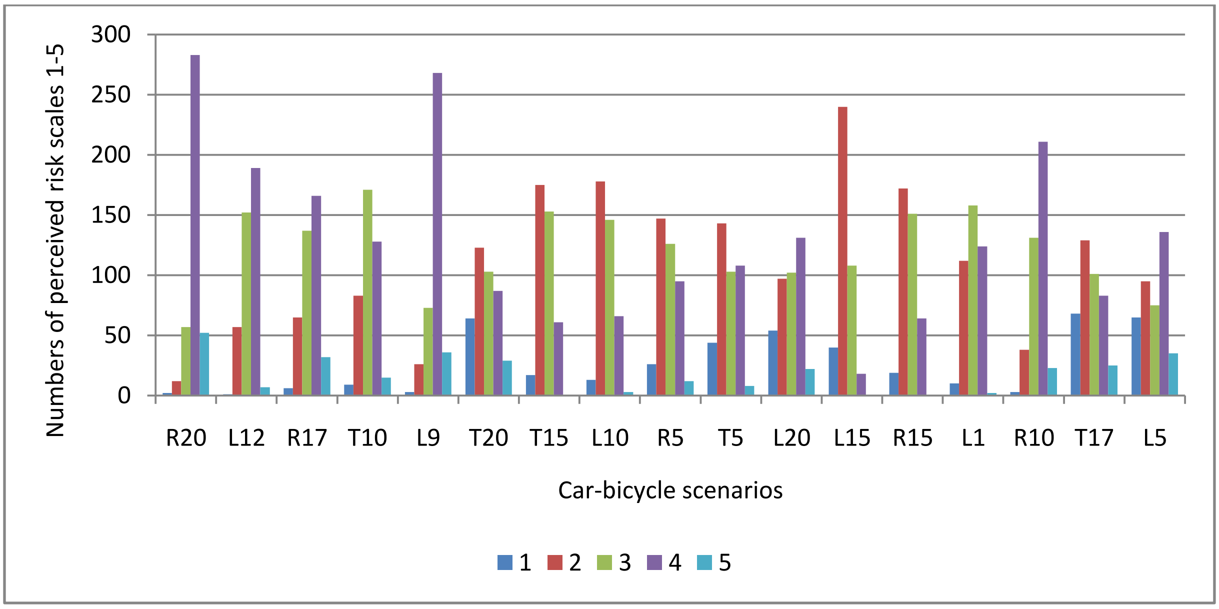


Figure 5-3 Perceived risk scales of the whole sample for each scenario: The scales 1-5 are used to rate the perceived risk; A higher scale indicates the higher perceived risk.

Among all scenarios, scenario R20 (right-turning car and through bicyclist) was assigned the most scale 5, followed by scenario L9 (left-turning car and through bicyclist in the wrong travel direction) and scenario L5 (left-turning car and right-turning bicyclist). When the risk of scenarios is evaluated by the frequency of the greatest scale, i.e. the scale 5, it can be presumably expected that the more the scale 5 are chosen for a scenario, the higher the probability that an accident is perceived to occur in the scenario. Accordingly, R20 was regarded as the most dangerous, followed by L9 and L5. When the scenario risk is evaluated according to the frequency of the smallest scale, i.e. the scale 1, the following correlation is also observable: the fewer the number of scale 1 are chosen for a scenario, the higher the probability that an accident occur in the scenario. Accordingly, the first three most dangerous scenarios were L12 (left-turning car and through bicyclist from the opposite direction), R20 and L9. This result did not match that accorded to the frequency of the greatest scale.

Not only the extreme scales but also the scales between them could be assigned to a scenario. The average values could better represent the perceived risk of a sample than the frequency of extreme scales. Therefore, the means of scales were used to measure the subjective risk in the following analysis.

5.4.2. Comparison between objective and subjective risk

Figure 5-4 presents the mean values of perceived risk scales. In this figure, the scenarios were arranged from left to right according to the ranking of the objective risk as shown in Table 5-1. As can be seen in this figure, the ranking according to the mean values did not match well with the objective ranking. In this figure, the mean values for the whole sample was included. Due to different characteristics between car drivers and cyclists, their risk estimation could be different. Thus, risk estimation was subsequently viewed separately for the two samples.

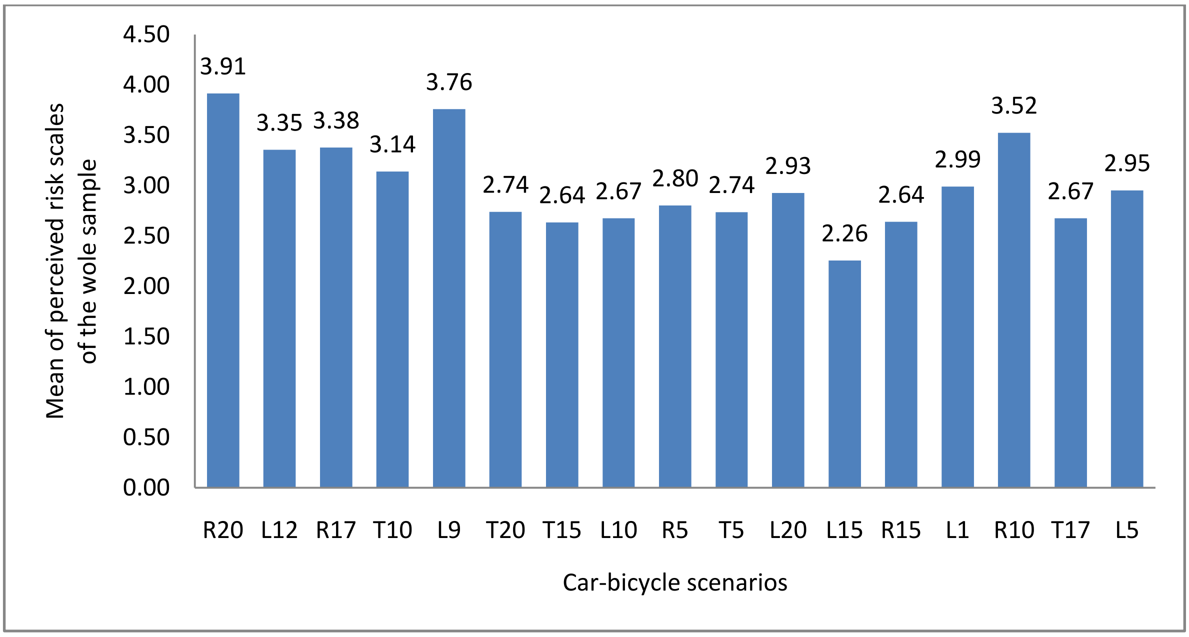


Figure 5-4 Mean of perceived risk scales of the whole sample

Table 5-1 presents the means and standard deviations of perceived risk scales and the rankings based on the mean values (subjective ranking) for the car driver sample and the cyclist sample, respectively. It also presents the accident frequency, objective risk class, and the ranking based on the accident frequencies (objective ranking) and the differences between the subjective ranking and the objective ranking.

As can be seen in Table 5-1, the subjective rankings did match well with the objective ranking for neither the car driver sample nor the bicycle sample. Scenario R20 was the only scenario, whose subjective ranking places by the two samples were consistent with the objective one. This scenario corresponded to the highest accident frequencies, while it corresponded to the greatest mean values of perceived risk scales by the two samples. Besides, the subjective ranking places of scenarios R5, L20 and R15 by the cyclist sample agreed with the objective ones. For all the other scenarios, there were some differences between the objective and subjective ranking places. In addition, the Spearman´s test revealed that there was no significant correlation between the subjective ranking and the objective ranking for the car driver sample (rho= 0.451, p = 0.069) and for the cyclist sample (rho= 0.331, p= 0.195). These results suggest that the perceived risk did not exactly match the objective risk. This finding confirms the results in most studies, in which the accuracy of subjective risk perception has been tested [132,194,195].

Table 5-1 Objective risk and subjective perceived risk of 17 car-bicycle scenarios

	Objective risk			Subjective perceived risk (scales)							
				Cyclists (n=197)				Car drivers (n=209)			
Scenarios	Accident frequency	Objective risk class*	Ranking	Mean	S.D.	Ranking	Diff.**	Mean	S.D.	Ranking	Diff**.
R20	3642	1	1	3.91	0.64	1	0	3.91	0.67	1	0
L12	2034	2	2	3.38	0.7	4	2	3.33	0.79	5	3
R17	886	3	3	3.31	0.88	5	2	3.44	0.91	4	1
T10	281	4	4	3.13	0.82	6	2	3.15	0.89	7	3
L9	249	4	5	3.66	0.71	2	-3	3.85	0.74	2	-3
T20	194	5	6	2.37	1.07	16	10	3.09	1.15	10	4
T15	182	5	7	2.68	0.81	12	5	2.59	0.76	15	8
L10	95	6	8	2.51	0.75	15	7	2.83	0.83	12	4
R5	39	7	9	2.79	0.96	9	0	2.82	0.98	13	4
T5	25	7	10	2.58	1.01	14	4	2.88	1.03	11	1
L20	15	7	11	2.72	1.15	11	0	3.12	1.11	8	-3
L15	11	7	12	2.24	0.71	17	5	2.27	0.68	17	5
R15	11	7	13	2.59	0.81	13	0	2.69	0.79	14	1
L1	10	7	14	2.79	0.85	8	-6	3.18	0.78	6	-8
R10	8	7	15	3.52	0.77	3	-12	3.53	0.77	3	-12
T17	2	7	16	2.67	1.16	14	-9	3.07	1.19	7	-9
L5	1	7	17	2.95	1.25	8	-7	2.78	1.23	10	-7

* The smaller class corresponds to the higher accident frequency or the higher objective risk.

** Difference between the subjective ranking and the objective ranking. Negative numbers correspond to overestimation, while positive numbers correspond to underestimation.

A discrepancy between perceived risk and objective risk has been found among cyclists and car drivers, when they were asked to assess whether bicycles or cars were more likely to be exposed to crashes [132]. Another inconsistency between perceived and actual risk has been found in assessing contribution factors for motorcycle accidents [194]. Lastly, only a moderate correlation has been demonstrated when comparing drivers´ risk assessments for selected locations on a driving route to the accident records at these locations [195]. An exception to these findings is the study of Carthy and Packham [196], in which there has been a statistically valid correlation between drivers´ perceptions of risk and overall accident frequencies, when the drivers assessed the risk of several routes that they had driven.

With regard to the ranges of differences between the objective and subjective rankings and the difference direction (under- or overestimation), they varied with different scenarios. For the scenarios in the objective risk classes of 1 to 6, which correspond to relatively higher accident frequencies, even small differences between the subjective ranking and objective rankings, such as, -1 or 1, were considered indication of over- or underestimation, since the accident frequency differences between these scenarios were mostly significant. The nine scenarios in the objective risk class 7 correspond to smaller accident frequencies (<100 over 11 years), and therefore the accident frequency differences between them were small. For these scenarios, the ranking difference of more than seven places was considered indication of over- or underestimation.

As a result, the overestimated scenarios by both samples were L9 (in class 4), L1 (in class 7), R10 (in class 7), T17 (in class 7, only by the cyclist sample) and L5 (in class 7). The scenarios, which were underestimated by both samples, included L12 (in class 2), R17 (in class 3), T15 (in class 5), T10 (in class 4), T20 (in class 5), and L10 (in class 6).

The general tendency of risk perception was that the respondents tended to overestimate the risk of scenarios, which correspond to smaller accident frequencies or higher objective risk classes, while they tended to underestimate scenarios, which correspond to higher accident frequencies or smaller objective risk classes. Scenario L9 was an exception that does not follow this tendency. This tendency could be explained to a certain extend by the relationship between risk perception and risky behaviors as described in the following text. (For ease of understanding, it is suggested to refer to Figure 5-1 while reading the following text.)

The overestimated scenarios, namely R10, L5, L1 and T17, all involve irregular/risky behaviors. Scenario R10 concerns a right-turning car and a left-turning bicycle from the same road side; L5 concerns a left-turning car and a right-turning bicycle from the same road side; L1 involves a left-turning car and a right-turning bicycle from the opposite direction. In R10, the cyclist that aims to take direct left-turning should have changed the lane to the right side of the car in advance. Likely, in scenario L5, the right-turning cyclist should have changed the lane to the right side of the car in advance. However, the cyclist has not. This is an irregular behavior or a risky behavior that causes conflicts. For scenario L1, the bicycle should have its separate space after right turning, such as a bicycle lane. Even if no bicycle lane is installed, the bicycle should ride on the right roadside. However, in L1, the bicycle crosses the traffic flow of motorized vehicles after right turning. This is also a risky behavior. Scenario T17 has the same feature. It concerns a through car and a through bicycle from the opposite direction but riding in the wrong direction. The cyclist in this scenario displays also an irregular or a risky behavior: the bicycle not only moves in the wrong direction, but also goes to the left side of the car in the traffic flow of motorized vehicles. The respondents, as indicated by overestimation, estimated these risky behaviors in the four scenarios to be more likely to cause accidents. Road users might have consciously avoided these scenarios caused by these behaviors. This might the reason why the corresponding accidents have occurred less frequently.

Some of the underestimated scenarios, such as L12, R17, T15 and T10, concern a common feature. That is, they are controlled by the right of way. A L12 accident occurs, when a left turning car crosses the path of a through bicycle from the opposite direction. In this scenario, the bicycle has the right of way. Scenario R17 concerns a right-turning car and a bicycle from the opposite direction but riding in the wrong travel direction. This scenario is evidently a conflict point. The bicycle, however, has the right of way following traffic rules, given that bicyclists are weaker and more likely to be injured in case of crashes with cars. The two scenarios have some common features: all concern a turning car and a through bicycle; they are all car-bicycle conflict points where both parties have to cross each other; the bicycle has the right of way. T15 and T10 are similar scenarios. T15 involves a through car and a left-turning bicycle from the opposite, and T10 involves a through car and a left-turning bicycle from the same roadside. The two scenarios are also conflict points, and the right of way is also regulated (but the car has the right of way). The accident cause analysis shows that the most common cause of accidents corresponding to the four scenarios was "mistakes made when turning" (mainly failure of yielding, i.e. giving the right of way) [13]. Following the relationship between risk perception and behaviors, due to the underestimation of both parties, the car drivers or cyclists, who have to give the right of way, could have not paid enough attention to observe the existence of the other parties. At the same time, the other parities have not cautiously predicted the failure of yielding. Consequently, the corresponding accidents have occurred more frequently.

In the other underestimated scenarios, i.e. T20 and L10, the car and the bicycle have to share the same space. Scenario T20 involves a through car and a through bicycle from the same roadside. In this situation, there should not be any conflict, when they go on their own paths. However, at intersections where bicycle crossings are not installed, the car and the bicycle have to share the space. This situation is not controlled by the right of way. The scenario L10 has the same feature. In L10, the car and the bicycle turn left from the same roadside. Normally, there is no separated space for direct-left-turning bicycles, and therefore they have to share the space. According to accident cause analysis, for scenario T20, the most common cause of cyclists in accidents was "incorrectly changing the lane when driving side by side or failure to observe the "zip method "", and that of car drivers was "mistakes made when overtaking (e.g. without sufficient lateral distance; at pedestrian crossings)" [13]. For L10, the most common cause for both cyclists and car drivers was "incorrectly changing the lane when driving side by side or failure to observe the "zip method"". Due to underestimation, one party might not have been cautious enough to choose accurate gaps in the traffic flow of the other party while going side-by-side or overtaking. Consequently, more corresponding accidents have occurred. Therefore, accidents corresponding to the underestimated scenarios might be decreased, when road users can more accurately perceive the risk of these scenarios, and thus behave more cautiously and take less risky behaviors.

However, the relationship between risk perception and behaviors cannot explain the situation of scenario R20, which was accurately ranked as the most dangerous scenario by both car drivers and cyclists. According to this relationship, car drivers should have paid enough attention to observe the bicycles, and cyclists should have especially cautiously expected the failure of car drivers´ yielding. As a result, not so many R20 accidents should have occurred. This might indicate that even if road users perceive the high risk of a scenario, the accidents could not be effectively reduced by their behavior adaptation. In R10 and L5 that are featured with risky behaviors, road users can adapt their own behaviors to avoid conflicts in these scenarios. However, R20 as well as R17, L12, L9 and T10 are conflict points, where cars and bicycles have to cross each other. Even if road users might take cautious and protective behaviors with accurate risk perception, their behaviors are affected by many other factors, such as personal mental, emotional and psychological elements, environment and intersection design.

5.4.3. Comparison between car drivers´ and cyclists´ risk perception

To compare the risk perception of the car driver sample and the cyclist sample, the mean values of perceived risk scales of the two samples are illustrated in Figure 5-5. As can be seen in this figure, car drivers estimated most scenarios, i.e. thirteen of seventeen, riskier than cyclists did. The scenarios, which car drivers estimated less risky than cyclists, were L12, T15 and T17. In scenario L12, the car turns left, and the cyclist goes straight over the crossroad from the opposite direction. The cyclist goes in the permitted travel direction. In T15, the car goes straight over the intersection, and the cyclist turns left from the opposite direction. The cyclist rides also in the permitted travel direction. In scenario T17, the car goes straight over the intersection, and the cyclist goes straight from the opposite direction. The cyclist goes on the left roadside opposite to the permitted travel direction. Simply according to the geometrical configuration and the traffic compliance status in the three scenarios, no reasonable explanation could be confirmed for why cyclists perceived higher risk for these three scenarios than car drivers did.

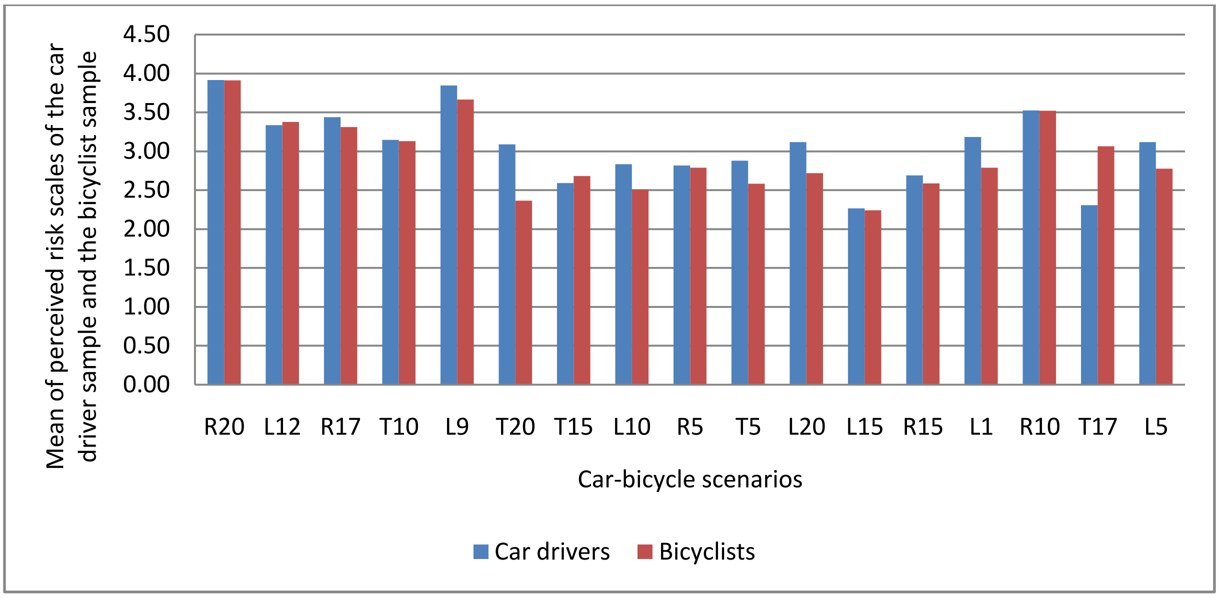


Figure 5-5 Mean of perceived risk scales of the car driver sample and the bicyclist sample

Among the thirteen scenarios that car drivers rated in a higher level in risk than cyclists, the differences were significant for eight scenarios as indicated by Mann-Whitney U test ($p<0.01$). Table 2 shows the Mann-Whitney U test results in comparing perceived risk scales of car drivers and cyclists for each scenario.

These results indicate that at signalized intersections cyclists in general perceive lower risk than car drivers do. This finding is in agreement with that in the study of Chaurand and Delhomme (2013), which has suggested that, in six dangerous situations, cyclist perceived lower risk than car drivers did. Considering, as discussed in section 5.1, that cyclists are objectively more likely to involve in car-bicycle accidents than cars at signalized intersections, this finding indicates that cyclists underestimated their risk at signalized intersections. As mentioned in Chapter 3, the accident cause analysis shows that cyclists should take the main responsibility for more than 50% of the accidents because of their adopted risky behaviors. Following the relationship between risk perception and behaviors, due to underestimation, cyclists might have been less cautious in interactions with cars, e.g. failing to yield, not signaling when turning, not checking traffic and tailgating in crossing signalized intersections. All of these behaviors presumably result in a higher probability of accident involvement. The high probability might be reducible, if cyclists could accurately perceive their risk at signalized intersections and thus take less risky behaviors.

Table 5-2 Mann-Whitney U test results in comparing risk perception scales of car drivers and cyclists: Ranking mean, Mann-Whitney U values and p values

Scenarios	$M_{Car\text{-}driver}$	$M_{Cyclist}$	Mann-Whitney U	p values
R20	202.67	204.38	20413	0.856
L12	202.26	204.81	20328	0.812
R17	212.35	194.11	18737	0.097
G10	204.3	202.65	20419	0.88
L9	217.78	188.35	17602	<0.01
G20	237.93	166.97	13390	<0.001
G15	196.94	210.46	19216	0.212
L10	223.63	182.14	16379	<0.001
R5	203.68	203.31	20549	0.973
G5	218.45	187.64	17463	<0.01
L20	222.38	183.47	16640	<0.01
L15	205.27	201.62	20217	0.722
R15	210.26	196.33	19175	0.2
L1	228.36	177.12	15391	<0.001
R10	201.71	205.4	20212	0.727
G17	167.71	241.47	13106	<0.001
L5	218.63	187.44	17424	<0.01

5.5. Conclusion and discussion

Risk perception (only for likelihood aspect) of car drivers and cyclists at signalized intersections was investigated in this chapter. Seventeen common car-bicycle interaction scenarios were first determined. An online survey was conducted to gather risk perception of a car driver sample and a bicyclist sample. Risk was rated based on a five-point Likert scale, which is a widely used measure of opinions in a great degree of nuance. The scales were used to indicate the subjective perceived risk for these scenarios.

No matter whether the subjective risk was evaluated by the frequencies of extreme scales or the mean values of scales, the results indicated that neither car drivers nor cyclists could accurately perceive the risk of these scenarios. The general tendency was that they overestimated scenarios with lower objective risks, and at the same time underestimated scenarios with higher objective risks. The tendency could be well explained by the relationship between risk perception and risky behaviors. Furthermore, the perceived risk of the car driver sample was compared with that of the bicyclist sample. The comparison indicated that cyclists tended to perceive thirteen of seventeen scenarios less risky than car drivers did. The differences were statistically significant for eight scenarios. In other words, cyclists extensively underestimated their risk at signalized intersections, considering that cyclists are objectively more likely to be involved in car-bicycle accidents at signalized intersections.

Nevertheless, the confirmed discrepancy between perceived and objective risk might still imply a possibility to mitigate accidents at signalized intersections e.g. through enhanced road user education and training. In this context, it is worthwhile to make car drivers and cyclists accurately perceive the risk of certain traffic scenarios, especially the underestimated scenarios, and to make cyclists more accurately aware of their significantly high risk at signalized intersections.

One limitation of this study is the fact whether the participants in the survey are a representative sample of Berlin traffic road users in terms of e.g. age, gender and driving/riding experiences is uncertain, although they were all from groups of Berlin residents. In the future work, a survey involving a representative sample is expected. Such a survey could be carried out in the city of Berlin, as well as in other countries or cities with different cycling cultures. Such a study allows not only the verification of the results from this study but also the study of influences of cycling cultures on risk perception. Another limitation is the fact that only the likelihood aspect of risk perception has been assessed. An additional survey is expected to cover risk assessment in relation to accident consequence aspect. In such a survey, possibilities of injuries instead of possibilities of collisions in the given scenarios should be rated. To obtain the objective risk, the data of both accident frequencies and accident consequences (i.e. injury severities of car drivers and bicyclists) should be analyzed.

6. Effects of bicycle facilities on car-bicycle crash risk at signalized intersections

Various studies have investigated the link between intersection factors and the bicycle crash risk at signalized intersections [147]. Despite these efforts, gaps in the current literature still exist. Safety effects of bicycle facilities have been studied using methods of e.g. before-after studies and case-control studies, but the results from these studies were mixed. Their safety effects are controversial especially at intersections. The reason for this could be that the context of bicycle facilities, i.e. intersection factors, is not simultaneously considered [31].

This chapter reviews Accident Prediction Models (APMs) for intersections. Comparing these models, the suitable regression model is chosen. It is used to associate intersection factors and the car-bicycle crash risk at signalized intersections based on the context in Berlin, where bicycle facilities have been widely installed. This work allows for estimation of safety effects of bicycle facilities at signalized intersections combining the effects of other intersection factors.

6.1. Model selection

With the application of APMs, different models have been developed. The following APMs were reviewed for intersections: the multiple logistic regression models, multiple linear regression models, Poisson regression models and negative binomial regression models [197]. All these models are used widely in traffic accident studies. However, they have their own limitations in their application.

The multiple logistic regression model is used to analyze binary accident outcomes. For example, an accident is a rear-end accident or a non-rear-end accident. However, many studies are to describe continuous accident outcomes, i.e. numbers of accidents. The multiple linear regression model can be used to describe continuous outcomes. However, the numbers of accidents are count data that are nonnegative numbers, yet the response variable in multiple linear regression analysis covers all numbers on a real interval, including negative numbers. We would like to comment that the multiple linear regression model is limited in describing adequately the numbers of accidents.

Due to the limitations of the two models aforementioned, this study chose the negative binomial regression model and the Poisson regression model, which are more suitable to describe nonnegative, discrete and random accidents events. The application of the Poisson regression model is also limited by the requirement of the equality of the expected value and the variance. Studies suggest that most accident data are over-dispersed. That is, the variance is significantly greater than the expected value. This limitation can be overcome by using the negative binomial distribution. The negative binomial model can be derived from the Poisson model. Whether the Poisson regression Model or the negative binomial regression model is more suitable in the assessment depends on the estimation result of the negative binomial dispersion parameter that is introduced in the process of derivation from the Poisson regression model to negative binomial regression model. The estimation result of the dispersion parameter is critical. If it is significantly different from zero, the negative binomial model is the appropriate choice; otherwise, a Poisson regression is suitable [148].

This study first used the negative binomial regression model to create the association between car-bicycle accidents and intersection factors. Depending on the estimation result of the dispersion parameter, it was decided whether the Poisson regression model would be used or not. This section introduces the Poisson regression model and the negative binomial regression model.

A Poisson distribution is expressed by

$$P(n_i) = \frac{\lambda_i^{n_i} e^{-\lambda_i}}{n_i!} \tag{6.1}$$

where i is the intersection index; n_i is the number of car-bicycle accidents at the intersection i; P is the probability of having n_i accidents. λ_i is the Poisson Parameter, which is equal to the expected accident number for the intersection i, i.e. $E(n_i)$. That is,

$$\lambda_i = E(n_i) = f_i p_i \tag{6.2}$$

where p_i is the risk that a bicycle involves in an accident with a car, and f_i is the traffic volume of bicycles across the intersection i.

The negative binomial model can be derived from the Poisson model as shown in Equation (6.1) by adding an independently distributed error term e^{ε_i} to the log transformation of Equation (6.2) [148], so that it can be get that

$$\ln \lambda_i = \ln(f_i p_i) + \varepsilon_i \tag{6.3}$$

Where e^{ε_i} follows the gamma distribution with the expected value of 1 and the variance of δ. It generates a conditional probability by submitting Equation (6.3) to Equation (6.1):

$$P(n_i \mid \varepsilon_i) = \frac{(f_i p_i e^{\varepsilon_i})^{n_i} e^{-f_i p_i e^{\varepsilon_i}}}{n_i!} \tag{6.4}$$

According to the law of total probability, the unconditional distribution of n_i is produced by integrating ε_i out of Equation (6.4). This distribution can be formulated as follows:

$$P(n_i) = \frac{\Gamma(\theta + n_i)}{\Gamma(n_i + 1)\Gamma(\theta)} \cdot \left(\frac{f_i p_i}{\theta + f_i p_i} \right)^n \cdot \left(\frac{\theta}{\theta + f_i p_i} \right)^\theta \tag{6.5}$$

where $\theta = 1/\beta$. This is a negative binomial distribution. Its expected value is equal to that of the Poisson distribution as shown in Equation (6.2). Its variance is

$$V(n_i) = E(n_i) + \delta E^2(n_i) \tag{6.6}$$

The negative binomial model allows that the expected value differs from the variance. In this way, the limitation of the Poisson model is eliminated. The variable δ is the negative binomial dispersion parameter.

The car-bicycle crash risk p_i is specified to be a function of intersection factors by use of the logistic equation.

$$p_i = \frac{e^{\beta X_i}}{1+e^{\beta X_i}} \tag{6.7}$$

where X_i is the vector of the considered intersection factors, and β is the vector of the corresponding estimated coefficients for each factor. The application of the logistic equation can constrain the value of p_i between 0 and 1. Furthermore, the sign of the estimated coefficient for each intersection factor corresponds to its effect direction. That is, a positive sign represents increasing effects and a negative sign represents decreasing effects on the crash risk.

By submitting Equation (6.7) to Equation (6.5), the probabilities of having n_i car-bicycle accidents at signalized intersections in relation to a set of intersection factors are obtained:

$$P(n_i) = \frac{\Gamma(\theta+n_i)}{\Gamma(n_i+1)\Gamma(\theta)} \cdot \left(\frac{f_i e^{\beta X_i}}{\theta(1+e^{\beta X_i})+f_i e^{\beta X_i}}\right)^{n} \cdot \left(\frac{\theta(1+e^{\beta X_i})}{\theta(1+e^{\beta X_i})+f_i e^{\beta X_i}}\right)^{\theta} \tag{6.8}$$

The effect coefficients are estimated using the maximum likelihood estimation approach by specifying a loss function in the module NONLIN in SYSTAT.

6.2. Intersection selection and dependent variable

A number of 140 four-way signalized intersections in Berlin were used as the sample. The sample intersections were selected from 205 randomly selected intersections, by excluding intersections where the considered intersection factors had been changed by constructions during the period between 2008 and 2013. The chosen intersections across the area of Berlin, and most of them are situated in the central area of Berlin.

The dependent variable, i.e. accident data, was obtained from the Berlin Police. It included all police-recorded car-bicycle accidents during the years from 2008 to 2013. The original database contained all bicycles accidents with different types of road users. Bicycle accidents involving passenger cars were extracted from the original database. 1,254 car-bicycle accidents were recorded at the 140 sample intersections.

6.3. Explanatory variables

A theoretical basis for choosing explanatory variables in application of APMs is rarely stated explicitly. In practice, analysis is constrained by data availability. However, the choice of variables should not be exclusively based on data availability. Normally, an analysis should include variables that

- Have been found in previous studies to exert a major influence on the number of accidents;
- Can be measured in a valid and reliable way;
- Are not very highly correlated with other explanatory variables included [179].

Considering that this study focused on crashes between bicycles and cars, intersection factors for cars and bicycles were contemplated. The following intersection factors were included in the model estimation:

- Car-specific factors: traffic volume of cars across intersections, speed limit on intersection approaches (for motorized vehicles), traffic signal phases, road markings (including centerlines/ raised medians, lane lines, left turning guide lines and directional arrows for turning);

- Bicycle-specific factors: traffic volume of bicycles across intersections, bicycle facilities (including bicycle paths and (advised) bicycle lanes), bicycle crossings, bicycle-specific traffic signals;
- Other factors: intersection size (measured by the number of traffic lanes), presence of trams and presence of bus stops.

Traffic volumes of cars and bicycles

The data of traffic volumes of cars and bicycles were provided by the Senate Department for Urban Development and the Environment (Berlin). The traffic volume measurement have been primarily conducted during the cycling season from March to November and lasted 12 hours from 7:00 to 19:00. The counts of traffic volume for an intersection have been carried out one to four times during the period between 2009 and 2013. When more than one count was available for an intersection, an average value was calculated.

In contrast to passenger cars, cycling activities are greatly dependent on weather situations, such as temperature, sunshine and rainfall. In order to make the bicycle volume data comparable, it is necessary to balance the data of bicycle traffic density according to weather conditions. The traffic volume data was balanced based on the standard weather situations, which was also provided by the Senate Department for Urban Development and the Environment (Berlin). The balancing factors included maximum temperature, sunshine duration, amount of rainfall, sunny days in the last week and rainy days in the last week.

Values for the other intersection factors were collected from Google Street View and Google Map. Each factor has its own symbols, and therefore their values can be easily obtained in this way.

Car-specific factors

Speed limit for motorized vehicles could be 5, 10, 15, 20, 30, 40, 50 and 60 in urban areas in Berlin. They are all multiples of 5 km/h. 50 km/h, as a default speed limit value, applies to the most roads in urban areas. 30 km/h is another frequent speed limit, and often posted in 30-zones. Very occasionally, speed limit of more than 50 km/h or less than 30 km/h is posted on intersection approaches. Therefore, 50 km/h and 30 km/h are two common speed limit values in data collection. Speed limit 50 km/h is default value, and generally not validated by speed limit signs. However, speed limit change (from 50 to 30 or from 30 to 50) is remarkably marked at intersections, as shown in Figure 6-1. Speed limit 30 km/h is widely posted in residential areas, and is validated by speed limit signs, as shown in Figure 6-1.

Figure 6-1 Speed limit signs for 50 km/h and 30 km/h

For each intersection approach, there is mostly only a signal phase with permissive left turns and permissive right turns. Sometimes, traffic light arrows are also set at intersections. Arrow lights assign the right of way, splitting the turning traffic from the through traffic and decreasing the conflict points in principle. An arrow light could be a right arrow, a left arrow or an up arrow, as shown in Figure 6-2. They indicate protected right-turning phase, protected left-turning phase or protected through phase, respectively. In data collection, the presence of protected signal phase was recorded.

Figure 6-2 Protected right-turning, protected left-turning or protected through signal phase

Road markings guide road users to use the roadways with minimized confusion. Road markings include center lines, lane lines, directional arrows for turning and left-turning guide lines, as shown in Figure 6-3. Center lines are used to separate traffic traveling in opposite directions. Lines for center lines could be solid lines, dashed lines or their combination. Lane lines separate the traffic traveling in the same direction. Lane lines are normally dashed lines. Directional arrows are marked on turning lanes, guiding through-going, left-turning and right-turning traffic into their relevant lanes. Left-turning guide lines are marked in the intersection areas guiding the left-turning traffic. Similar to center lines, raised medians present physical barriers also to separate the opposite motor vehicles, as shown in Figure 6-3. Raised medians could be vegetation, parking plot or tram tracks. In data collection, the number of approaches, on which different road lines have been marked and raised medians have been installed, were recorded.

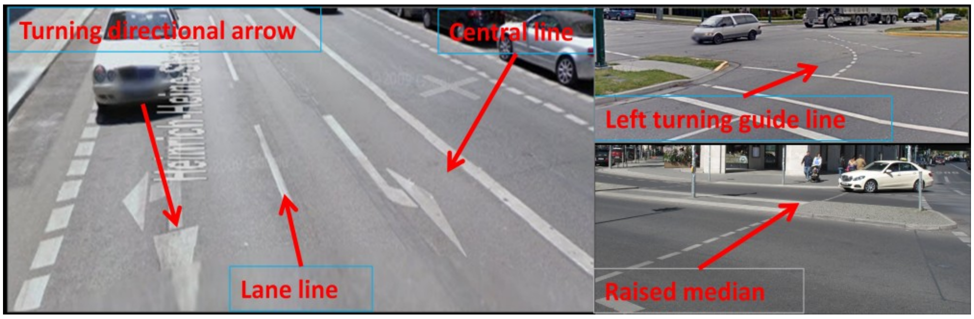


Figure 6-3 Road markings and raised median

Bicycle-specific factors

Figure 6-4 Bicycle facilities

Bicycle facilities are relatively well developed in Berlin. The Berlin cycling network covers bicycle paths, bicycle lanes, advised safety lanes, shared bus/bike lanes and combined pedestrian/bike paths, as shown in Figure 6-4. When no bicycle facilities exist, bicycles share roadways with motor vehicles. Bicycle facility types are distinguished based on whether and how bicycles are separated from motor vehicles or pedestrians. Bicycle paths physically separate bicycles from motorized vehicles. Bicycle paths are exclusively for bicycles, featuring the biggest separation degree. Bicycle lanes visually separate bicycles from motorized vehicles by solid lines. Bicycle lanes are also exclusively for bicycles. Similar to bicycle lanes, advised safety lanes also visually separate bicycles from motorized vehicles but by broken lines. However, advised safety lanes are allowed to be driven on by motor vehicles in some conditions. On shared bus/bike lanes, bicycles are allowed to share road lanes with buses. Pedestrian/bike paths are built on sidewalks, on which bicycle and pedestrians share the same space. Furthermore, in some locations there exist short but dedicated lanes just prior to intersections, which is called "short advised safety lane". In data collection, bicycle facility types were recorded on both intersections entering and departure approaches.

Bicycle crossings are located adjacent to pedestrian crossings, marked by dashed lines or red pavements, as shown in Figure 6-5. In data collection, the presence of bicycle crossing was recorded for each entering approaches.

Figure 6-5 Bicycle crossing and bicycle-specific traffic signal

An independent traffic signal device indicates bicycle-specific traffic signals, as shown in Figure 6-5. The device is often installed besides the traffic signal for motor vehicles or pedestrians. It is relatively smaller than traffic light device for motor vehicles and pedestrians, and has three phases: red, yellow and green. In data collection, presence of bicycle-specific traffic light was recorded for each entering approach.

Other factors

Intersection size was simply measured by the number of road lanes on intersection approaches, including parking lanes, bicycle lanes, traffic lanes for motor-vehicles and raised medians. In data collection, road lane numbers were recorded for each intersection approach. When no center lines and lane lines were present, the intersection size was counted just by estimating how many motor vehicle flows are allowed go through in parallel at the same time.

Figure 6-6 Bus stop and tram track

Bus stops could be installed on both entering and departure approaches. In data collection, the presence of bus stops was recorded for each approach. Tram is an additional transport mode in Berlin. It takes charge of a considerable part of public traffic with convenience and lower environmental pollution. In data collection, the presence of tram is recorded for an intersection. Examples of bus stops and tram tracks are shown in Figure 6-6.

Table 6-1 Summary statistics for selected intersections

No.	Factors	Min	Max	Mean	S.D.
	Dependent variable				
	Accident numbers from 2008 to 2013	0	33	9.02	8.09
	Independent variables				
	Car-specific factors:				
1	Traffic volume of cars (Counts/12 h)	3705	62428	27605.17	11582.45
2	Number of approaches with speed limit of 30 km/h	0	4	0.43	0.82
3	Presence of protected signal phase (yes: 1; no: 0)	0	1	0.24	0.43
4	Number of approaches with centerlines (including raised medias)	0	4	3.71	0.69
5	Number of approaches with lane lines	0	4	3.05	1.39
6	Number of approaches with left turning guide lines	0	4	1.86	1.53
7	Number of turning lanes	0	4	2.12	1.46
8	Number of approaches with raised medias	0	4	2.51	1.51
	Bicycle-specific factors:				
9	Traffic volume of bicycles (Counts/12 h)	124	9330	2568.58	1788.47
10	Number of approaches with bicycle paths	0	8	3.99	2.90
11	Number of approaches with bicycle lanes	0	6	0.50	1.27
12	Number of bicycle crossings	0	4	2.50	1.62
13	Number of approaches with bicycle-specific traffic signals	0	4	1.49	1.64
	Other factors:				
14	Intersection size (number of traffic lanes on four intersection approaches)	8	44	24.41	7.65
15	Presence of trams (yes: 1; no: 0)	0	1	0.11	0.32
16	Presence of bus stops (yes: 1; no: 0)	0	1	0.63	0.48

To better understand the collected data in this study, the values of the dependent and independent variables are presented in Table 6-1.

6.4. Correlation analysis

In application of the multivariate analysis, it is assumed that the investigated factors are mutually independent.

This is aimed at avoiding the multicollinearity phenomenon [198]. To eliminate this problem, a correlation analysis was carried out between the selected factors as showed in Table 6-1. The analysis result indicated that all factors of road markings, except the number of central medians, and the intersection size, were subject to strong or moderate correlations (with correlation coefficients more than 0.4) with the traffic volume of cars. The number of bicycle crossings and the number of approaches with bicycle-specific signals were strongly correlated with the number of approaches with bicycle paths with coefficients more than 0.5.

After eliminating the factor combination that could result in multicollinearity, the following factors were included in the final coefficient estimation:

- traffic volume of cars (factor No. 1, correlated with factor No. 14, as indicated in Table 6-1)
- number of approaches with speed limit 30 km/h (No.2)
- presence of protected signal phase (No. 3)
- number of central lines (including marked lines and raised medians) (No. 4, correlated with factors No. 5, 6, 7 and 8)
- number of approaches with bicycle paths (No. 10, correlated with factors No. 12 and 13)
- number of approaches with (advised) bicycle lanes (No. 11)
- presence of trams (No. 15)
- presence of bus stops (No. 16)

The correlations between these factors are shown in Table 6-2. It can be seen that they are weakly correlated with coefficients less than 0.4.

Table 6-2 Correlation between the estimated intersection factors

	No. 1	No. 2	No. 3	No. 4	No.10	No. 11	No. 15	No. 16
Traffic volume of cars (No. 1, correlated with No. 14)	1							
Number of approaches with speed limit of 30 km/h (No. 2)	-0.331	1						
Presence of protected signal phases (No. 3)	0.227	-0.146	1					
Number of central lines (No.4, correlated with No. 5,6, 7 and 8)	0.27	-0.207	0.162	1				
Number of approaches with bicycle paths (No. 10, correlated with factors No. 12 and 13)	0.297	-0.246	0.258	0.267	1			
Number of approaches with bicycle lanes (No. 11)	-0.003	-0.083	0.1	0.061	-0.267	1		
Presence of trams (No. 15)	-0.049	0.031	0.277	0.087	0.032	0.071	1	
Presence of bus stops (No. 16)	0.118	-0.121	-0.026	0.102	-0.022	0.059	-0.096	1

6.5. Results and discussion

Eight independent variables were investigated in the negative binomial regression model. The estimated coefficients for each factor and the significance levels are presented in Table 6-3. The signs of the estimated coefficients directly state their effect directions on the crash risk p_i.

The estimated value of the reciprocal of the negative binomial dispersion parameter, i.e. $\theta = 1/\beta$, is 2.975 at a significant level (p<0.001). This indicates that the negative binomial regression model is suitable for this study over the Poisson regression model.

Table 6-3 Estimation results of the negative binomial regression

Parameter	**Estimated value** θ	***t***	***p*-value**
Constant	-6.833	-17.277	<0.001
Traffic volume of cars (Counts/12 h)	2.111E-4	3.528	<0.001
Number of approaches with speed limit of 30 km/h	-0.103	-1.194	0.12
Presence of protected signal phase	0.113	0.744	0.23
Number of approaches with bicycle paths	0.043	1.768	<0.05
Number of approaches with (advised) bicycle lanes	-0.084	-1.656	<0.05
Presence of trams	0.009	0.049	0.48
Presence of bus stops	-0.035	-0.266	0.395
Number of central lines (including raised medians)	0.135	1.33	0.092
θ (Reciprocal of the negative binomial dispersion parameter β)	2.975	5.605	<0.001
Number of observation	140		
Restricted log-likelihood (constant only)	-431.996		
Unrestricted log- likelihood	-411.624		
Likelihood ratio index	0.04		

Three of the eight factors are significantly related to the crash risk p_i. Traffic volume of cars was found to increase car-bicycle crash risk. This result is consistent with studies that have modelled associations between intersection factors and bicycle accidents at signalized intersections [155-157]. The average daily numbers of motorized vehicles is an important predictor of bicycle crashes, since the traffic flows affect the accident frequency to a very large extend. This relationship has been also indicated by a summary of related studies [199]. Actually, there is a nonlinear relationship between the traffic volume of motorized vehicle flows and the cyclist crash risk. That is, the crash risk increases with the increment of traffic volume of motorized vehicles to a certain level and then decreases. However, due to the specific model structure in this study, this non-linear relationship cannot be illustrated.

Regarding bicycle facilities, the factors of (advised) bicycle lanes and bicycle paths were found to be significantly associated with the crash risk. A bicycle is less likely to involve in an accident with cars, when more bicycle lanes are installed at intersections. The positive effects of bicycle lanes on cycling safety was also suggested by a study, in which safety effects of bicycle lanes were studied at intersections combining other intersection factors (the second-stage study in [32]). In contrast, a bicycle is more likely to collide with cars, when more bicycle paths are installed on intersection approaches. Although safety effects of bicycle paths are controversial, it is commonly accepted that bicycle paths might hamper visual interactions between cyclists and motorized vehicle drivers at intersections. For this reason, a number of intersection modification measures for bicycle paths have been proposed and conducted. These intersection modification measures are summarized in a literature review [154]. In Berlin, some measures have been applied, such as coloured (red) bicycle crossings, conversion of bicycle paths to bicycle lanes in the immediate area of intersections, to bring bicycle paths closer to the motorized traffic before intersections, and an advanced (i.e. forward moved) stop line for bicycles. At all sample intersections with bicycle paths, stop lines for bicycles have been placed in the front of stop lines for motorized vehicles. At most sample intersections, bicycle paths have been brought closer to motorized traffic lanes. The finding indicates that these bicycle-path modification measures cannot effectively decrease the negative effects of bicycle paths at intersections. To be able to assess effectiveness of different intersection modification measures for bicycle paths deserves further studies.

The associations of the other five factors with the crash risk are not significant. More central lines (including raised medians), the presence of trams and the presence of protected signal phase increase the crash risk in an insignificant level, while the number of approaches with speed limits of 30km/h and the presence of bus stops are insignificantly positively associated with the cycling safety.

Central lines of roads and raised medians guide the movements of cars. Moreover, raised medians provide bicyclists with refuges to stay on in crossing intersections. These views seem to add advantages on their safety effects. The insignificant effects could be explained by "risk compensation" of bicyclists, i.e. underestimation of the crossing task by cyclists [200]. Another explanation could be: At signalized intersections, a bicyclist on refuges usually needs to wait for a green phase to continue crossing the intersection. It usually lasts so long that a bicyclist is more likely to lose his patience and continues to proceed through at red light. Protected signal phases have both positive and negative safety effects: In protective signal phases, car drivers can better observe driving environment, especially the presence of bicycles. However, protected signal phases can extend the period of a phase cycle, which could increase possibilities of red-light-violation by bicyclists. For this reason, the effects of protected signal phases are insignificant. Intersections with bus stops are usually busier, with more complex traffic behaviours. The presence of bus stops seems to increase crash risk. However, the presence of a bus stop might make car drivers drive more slowly, increasing searching time and driving caution. Therefore, only insignificant effects of the presence of bus stops are found.

Car drivers driving at lower speed, e.g. 30km/h, that is lower than the default speed limit of 50km/h, can better observe the presence of bicycles, and have more time to react to bicycles that they have to interact with. In the used intersection sample, only a small number of intersections have been posted with signs demanding speed limit of 30km/h (44 of 140). Therefore, there is not enough evidence to establish a positive or negative association. This may explain why significant effects of low speed limit were not found. Tram tracks could deteriorate road surface conditions, and tram cars could worsen visibilities between bicyclists and car drivers. It seems that presence of trams could increase the car-bicycle crash risk. The low proportion of sample intersections with trams (16 of 140) might be also a reason why significant negative safety effects of trams were not found. At intersections with tram traffic in Berlin, all other traffic is assigned with red lights, while tram cars are crossing intersections. Under this kind of traffic signal control, the behaviors of car drivers and bicycles is be little affected by the tram traffic. This might be another possible reason for the non-significant safety effects of trams.

6.6. Conclusion

This chapter focused on 140 four-way signalized intersections in Berlin, providing a big range of car traffic, bicycle traffic as well as car-bicycle accident counts. This study proposed a negative binomial regression model by introducing a logistic equation. The aim was to determine safety effects of bicycling facilities on car-bicycle crashes combining other intersection factors. The coefficients of considered factors were estimated by use of the maximum likelihood approach. This study found that the negative binomial regression model was suitable over the Poisson regression model for estimating the probability of car-bicycle crashes, because the coefficient of over-dispersion was significantly different from zero.

The estimation result indicated that higher traffic volumes of cars are significantly associated with a higher risk that a bicycle collides with a car. This finding is in accordance with past studies. Presence of bicycle facilities at intersections was found to have significant effects on the car-bicycle crash risk, too. Intersections with more approaches with bicycle lanes are associated with a lower crash risk. In contrast, intersections with more approaches with bicycle paths are associated with a higher crash risk, even if intersection modifications have been applied for bicycle paths. This finding means that further studies are deserved to investigate the effectiveness of different intersection modification measures for bicycle paths, such as coloured bicycle crossing, bike boxes and conversion of bicycle paths to bicycle lanes in advance of intersections.

This study is presented within a limitation. Although this study used a considerable number of sample intersections, the sample was not representative of the total population of intersections. A representative sample of intersections is expected to be covered in future studies. This will help to generate more solid conclusions related to e.g. the effects of presence of trams and number of approaches with lower speed limit.

7. Conclusion and outlook

Bicyclists are among the most vulnerable road users. Especially at intersections, a considerable number of bicycles collide with passenger cars despite the control of traffic signals. This thesis has been concerned with car-bicycle safety at signalized intersections. The objective of this thesis is to find out answers to the question: what can be done to improve car-bicycle safety at signalized intersections. To answer this question, a multi-disciplinary study has been carried out based on the context of Berlin. That is to investigate car-bicycle safety at signalized intersections from multi-aspects.

As the foundational work, historical accident data was first analyzed with regard to accident scenario frequencies, causation, consequences and time. From the human aspect, car-bicycle interactions at signalized intersections were recorded and analyzed by creating a Quasi-NDO framework. Also from the human aspect, risk perception of road users was investigated for common car-bicycle scenarios at signalized intersections by use of an online survey. From the infrastructural aspect, effects of bicycle facilities on car-bicycle crash risk at signalized intersections were evaluated using the negative regression model. The findings in these studies have delivered implications to improve car-bicycle safety at signalized intersections, which are summarized in this chapter.

Car-bicycle safety at signalized intersections is a big theme. Besides the aspects that have been involved in this thesis, much other work could be carried out. In this chapter, additional work is recommended to address potential crash mitigation strategies from other aspects.

7.1. Findings and implications in this research

7.1.1. Car-bicycle accident analysis

To prevent accidents, it is necessary to know accidents. Given that accident analysis particularly on car-bicycle accidents at signalized intersections is absent in the past studies, two databases were first analyzed in this thesis to investigate characteristics of car-bicycle accident at signalized intersections. The two databases were the Berlin police-reported accident data over eleven years (13,036 accidents) and the GIDAS accident data over nine years (469 accidents).

Scenarios, which are a widely used accident category to analyze accidents, were defined for car-bicycle accidents at signalized intersections. Frequencies of each accident scenario were determined based on the two databases. The analysis results found that the most common accident scenario was a right-turning car colliding with a through bicycle in the same direction, with shares of 28% in the police database and 19% in the GIDAS database.

The police-reported database was analyzed concerning causation. The causation analysis showed that:

- The most common cause for car drivers was mistakes in right turning. That is, car drivers failed to give the right of way to bicycles.
- The most common cause for cyclists was unlawful use of roadways, including running in the wrong direction and using other parts outside the bicycle crossing in crossing intersections.

- The second common accident cause was red-light-violation for both car drivers and cyclists.

Bases on the police-reported database, analysis was conducted with regard to consequences and time. As 97% of observed casualties were found to be bicyclists, their vulnerability in road accidents seems undeniable. Furthermore, highly visible was the effect that the respective season had on the frequency of bicycle accidents. This was not so much due to a direct influence of a particular weather situation, but rather and on a grand scale, due to an observed seasonal oscillation in the density of bicycle traffic volume.

The accident analysis in this work presents a typical picture of car-bicycle accidents at signalized intersections in a bicycle city/country. Berlin is a bicycle city with a high bicycle modal share of up to 13%. GIDAS accident data is regarded as being representative for German, which is in the top three of European countries in terms of bicycle use with a bicycle modal share of up to 10%. This is one important contribution of this work. As another important contribution, the analysis results provide necessary statistics for the other work in this thesis.

Two implications can be extracted from the findings in this work. Both used databases indicated that the most frequent scenario was R20, in which the car turns right and the bicycle goes through the intersection. Specific studies focusing on the scenario R20 are suggested to be of great significance for the improvement of car-bicycle safety. Motivated by this implication, visual interactions between car drivers and bicyclists in this scenario were studied in this thesis, which is introduced in the following section. Another important implication concerns the accident cause of red-light-violation. The analysis of accident causes showed that the second most frequently recorded accident cause was red-light-violation for both car drivers and bicyclists. The lateral accidents caused by red-light-violation are well-known and have been concerned in many researches. However, a considerable number of longitudinal accidents have occurred when bicyclists go through the red light of the bicycle-specific traffic signal. With the increasing installation of bicycle-specific traffic signals, more attention and studies for bicycle-specific traffic light violation are suggested in future research work, e.g. on the aspects of light design, visibility, coordination with other traffic lights and road users´ adaption to the lights.

7.1.2. Quasi-NDO study

The method of NDO is proved reliable and efficient to capture, store and analyze traffic conflicts. Traffic conflicts are regarded as a surrogate for accident data analysis for safety diagnosis. However, few NDO studies have investigated interactions between car drivers and bicyclists. Several NCO studies have focused on interactions between car drivers and bicyclists, but from perspective of bicyclists. The accident cause analysis indicated that car drivers were responsible for more accidents than bicyclists were. This thesis carried out a Quasi-NDO study to investigate interactions between car drivers and bicyclists at signalized intersections from perspective of car drivers.

With the aid of an instrumented car, participants were recruited to drive a preset route in real traffic. Interactions between car drivers and bicyclists were recorded from perspective of car drivers. By use of both automated conflict detection based on a deceleration trigger and manual conflict detection through video observation combining the dynamical data and the eye movement data, car-bicycle conflicts at signalized intersections were detected. By the automated conflict detection, only one conflict was detected. In contrast, the manual conflict detection identified 121 possible conflicts, in which car drivers or bicyclists had to react to the other to avoid unwanted consequences. Three events among these detected possible conflicts were found to be safety-critical, and revealed two safety-critical situations: the first situation concerns a right-turning car and a through-bicycle behind parked cars; the second situation concerns a right-turning car and a bicycle coming from the right road. This is one important finding in this work.

The detected possible conflicts were typed into car-bicycle scenarios. The first three most frequently occurring car-bicycle scenarios in these conflicts were essentially consistent with that indicated by the GIDAS accident data and that indicated by the Berlin police-reported accident database. As a reminder, the R20 scenario corresponds to the most frequent car-bicycle conflicts/accidents at signalized intersections. Considering that eye movement data can provide safety-related evidence about visual attention, the recorded eye movement data (i.e. gaze location) of car drivers was analyzed for 146 collected events of R20 scenario. The scenario R20 was categorized into six R20 sub-situations on a basis of the sequences of the car´s and the bicycle´s arriving at intersections and the traffic light phases. According to the distribution of gaze locations in these sub-situations, two sub-situations were seen as more likely to result in conflicts or even crashes. By observing the gaze location distribution, it is suggested that the crash risk in the two sub-situations could be decreased by appropriate modifications of bicycle facilities at intersections (to make bicycles more visible for car drivers) and enhanced road user education (e.g. to emphasize the importance of shoulder and mirror check). The aim of these measures is to increase generally car drivers´ awareness of the co-existence of bicycles as road users. This is the second important finding in this work and the implication from this finding.

Another finding regarding eye movements focused on car drivers´ mean fixation durations on per through bicycle in the scenario R20. It indicated that the car drivers spent more time fixating on the through-bicycles, if they were involved in a conflict. However, mean fixation durations were not influenced by the presence of oncoming bicycles, right-turning bicycles, pedestrians in conflicting crosswalks and cars ahead.

This work created a framework for studies of car-bicycle interactions at signalized intersections. Concerning the conflict detection method, the automated conflict detection based on a trigger of an extreme value could miss conflicts, since not all conflicts are accompanied with extreme values. The manual conflict detection could effectively identify conflicts by observing videos with gaze location data and dynamic data. One reason was that the gaze location data supplied important information to understand the motivations of car drivers´ behaviors. Another reason was that the related data at signalized intersections could be easily positioned according to the geographical data, so that it was unnecessary to observe the videos frame-by-frame. It saved a great amount of time.

However, only two safety-critical situations were revealed in this work, because this was a small-scale study. In addition, the conclusions on eye movements need to be confirmed due to the limited number of participants. Therefore, a larger-scale study is expected in the future work to involve longer data collection time and more participants. For such a study, the created framework can be applied. It can be said to be another important contribution of this work. To obtain more achievements in the future work, some improvements are suggested for the framework:

- A new version or a new type of the eye-tracking headset should be achieved due to the sensitivity of the used eye-tracking headset to its location change relative to the eye.
- Digital maps with signalized intersection locations for areas in which participants drive should be available for the manual conflict detection.
- The study should be organized in a more natural way: participants´ own cars could be instrumented and participants could decide where and when to drive.

7.1.3. Risk perception for car-bicycle scenarios

Risk perception is a crucial indicator for human behaviors. The general relationship is that the less one perceives risk in a given situation, the more likely he or she is to adopt risky behaviors and therefore the more likely he or she is to be involved in crashes. Through an online-survey, the risk of seventeen common car-bicycle scenarios at signalized intersections were scaled by car drivers (N=209) and cyclists (N=197) alike. The responses from this survey were used to evaluate the subjective risk perception. Accident frequencies that were achieved in the work of accident analysis were used to evaluate the objective risk of these scenarios.

The obtained values of subjective risk and objective risk were compared. The results indicated that both car drivers and cyclists inaccurately perceived the risk of these scenarios. The general tendency was that they overestimated most of the scenarios with lower objective risks, and underestimated most of scenarios with higher objective risks. This is the first important finding in this work.

Furthermore, the obtained values of subjective risk of car drivers and cyclists were also compared. Astonishing, cyclists tended to perceive most scenarios less risky than car drivers. Considering that cyclists are objectively more likely to be involved in car-bicycle accidents at signalized intersections, they underestimated their risk at signalized intersections. This is another important finding in this work.

The tendencies could be explained to a certain extent by the relationship between risk perception and behaviors. These discrepancies between perceived and objective risk could play a role in crash occurrence. It implies the possibility to reduce accidents by making both car drivers and cyclists more accurately perceive the risk of these scenarios and making cyclists more accurately perceive their risk at signalized intersections. One way of achieving this could be through enhanced road user education and training.

Nevertheless, only likelihood aspect of risk was taken into account in risk evaluation. Given that perceived risk includes two aspects, namely likelihood and consequence of an accident, risk evaluation could be investigated also in relation to the consequence aspect in the future work.

7.1.4. Safety effects of bicycle facilities

Safety effects of bicycle facilities are controversial especially at intersections. One reason for that could be that the context of bicycle facilities, i.e. other intersection factors, is not simultaneously considered. The association between car-bicycle crash risk and intersection factors was described by use of the negative binomial regression model. The negative binomial regression is a derived version of the Poisson model, which is usually the first choice in modelling traffic accidents, but can remove the constraint of the Poisson model. This association was created based on six-year accident history at 140 signalized intersections in Berlin. In this way, safety effects of bicycle lanes and bicycle paths at signalized intersections were evaluated combining the effects of other intersections factors, including traffic volume, geometric data and both bicycle-specific and car-specific infrastructure.

The estimation results showed that the intersections with more approaches with bicycle lanes resulted in a lower crash risk, while the intersections with more approaches with bicycle paths had a higher crash risk, even if intersection modifications have been applied for bicycle paths. This finding implies that further studies are deserved to investigate the effectiveness of different intersection modification measures for bicycle paths, such as coloured bicycle crossing, bike boxes and conversion of bicycle paths to bicycle lanes in advance of intersections.

7.2. Limitation and future work

The studies in this research were primarily based on the context in Berlin. The historical accident data analysis was based on the Berlin Police-reported accident data. The car-bicycle interaction data was collected while participants were driving in traffic of Berlin. The data of risk evaluation for common car-bicycle scenarios was gathered from traffic road users in Berlin. The model to associate car-bicycle risk and intersection factors was solved based on a sample of signalized intersections in Berlin. Berlin is a typical bicycle-city, equipped with well-built bicycle facilities and advocated by cycling strategies. In Berlin, cycling is becoming more and more attractive. In the last years, the share of cycling in the routes traveled in the city has been increased by up to 50%. In 2008, the bicycle modal share in Berlin was 13%, even higher than the average bicycle modal share of 10% in Germany. It is uncertain whether the findings in this research are applicable to other cities or countries with different cycling culture. This is a big limitation of this research. However, it, at the same time, implies a good chance to carry out the same studies in other cities and countries. Such studies would verify the findings in this research and study the influences of different cycling culture on the corresponding research topics.

In most accident models for road traffic, human, environment (including infrastructure) and vehicles are the elementary components of the road traffic system. This research has been concerned with the human aspect, such as car-bicycle interactions and perceived risk of road users, and the infrastructural aspect, such as safety effects of bicycle facilities. With regard to the vehicular aspect, much can be done for cycling safety improvement.

The number of electric bicycles has increased in the last years, due to the ease of movement while driving an electric bicycle. The total number of electric bicycles in Germany has grown to 2.1 million, taking the market share of 12.5% in bicycles. Although it is not mandatory, electric bicycles often share infrastructure with conventional bicycles. Differences between conventional bicycles and electric bicycles in their use (such as speed, infrastructure choice and over-taking behaviors), critical situations and accident situations are of great interest in current research. However, to answer the questions, such as whether and how the mixed traffic with electric bicycles would increase the risk of conventional bicycles, and whether it is necessary and what can be done to adapt existing infrastructure to the use of electric bicycles, deserves more efforts.

With the popularity of electric bicycles, cycling assistance systems, such as Antilock Braking System (ABS) and Braking Dynamics Assistance system (BDA) that are commonplace for motorized vehicles, is being introduced for electric bicycles. These systems are promising to enhance cycling safety. However, adaptation of these systems is still needed for their effective application in bicycles.

In recent years, Intelligent Transport Systems (ITS) have assisted in decreasing road traffic fatalities. Some ITS specially address cyclists, such as Blind Spot Detection, Intersection Safety, Pedestrian and Cyclist Detection System + Emergency Braking and VRU Beacon System. They have been assessed to affect cyclist safety in a positive way by preventing fatalities and injuries [197]. From a safety viewpoint, cyclists have, however, less benefited from ITS than passenger car occupants, since vulnerable road users have not been that much in focus when developing ITS. In the future development planning work, more consideration is recommended to address cyclist safety and to integrate cyclists in ITS on a higher level. Meanwhile, some questions should be taken into consideration in the development and adaptation process of ITS, such as:

- What can be done to improve the reliability, utilities and efficiency of an innovative ITS solution?
- How can the public and political acceptance of ITS be improved?
- How do ITS impact road users´ behaviors?

Autonomous cars are claimed to be inevitable, and to be promising to improve road traffic safety, supported by advanced sensor techniques and control systems. Nowadays, the development of autonomous cars is still facing the challenge in detecting and reacting to cyclists. The reasons are that bicycles are small and nimble, they have more variance in appearance, e.g. shape, color, people hang stuff on them, and bicyclists´ behaviors are unpredictable. Whether more machine learning, by putting more images of cyclists into the cars, could solve this problem, is for now unknown. One possible solution could be Bicycle to Vehicle communications, in which bicyclists also join the party by communicating their positions and intentions with autonomous cars. However, the posed financial and logistical questions should be first answered, such as who pay for the system, how it is developed and enforced, and whether traffic laws should be changed. In addition, the question whether and how cyclists respond differently to autonomous cars from manually-driven cars should be noted and answered.

To improve cycling safety, the cooperation and coordination of stakeholders in different fields is indispensable. The stakeholders are to be found in the fields of Engineering, e.g. improvement of bicycle infrastructure, and development of Advanced Driver Assistance System, Education, e.g. driving and cycling training education for appropriate behaviors, and Enforcement, e.g. the formulation of traffic rules, and legislation. The practical implementation, however, requires not only substantial political and financial support, but also individual acceptance and adherence to it by all road users.

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models-for-road-intersections.pdf.
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List of Figures

List of Tables

Appendix 3.1

The List of accident causes applied by the Berlin police-reported accident database.

Driving fitness:

01 Influence of alcohol

02 Influence of other intoxicating substances (e.g. drugs, narcotics)

03 Overfatigue

04 Other physical or mental faults

Improper driving:

Use of the road

10 Use of wrong carriageway (or lane) or unlawful use of other parts of the road

11 Violation of the rule of driving on the right side

Speed

12 Unadapted speed and exceeding at the same time the speed limit

13 in other cases

Distance

14 Insufficient safety distance (Other causes leading to a traffic accident should be allocated to the respective positions, such as speed, overfatigue, etc.)

15 Abrupt braking without compelling reason by the vehicle in front

Overtaking

16 Unlawful right-hand overtaking

17 Overtaking in spite of oncoming traffic

18 Overtaking in spite of unclear traffic situation

19 Overtaking in spite of insufficient visibility

20 Overtaking without observing the rear traffic and/or without timely and clearly indicating the intention to swerve out

21 Mistake made when returning to right lane

22 Other mistakes made when overtaking (e.g. without sufficient lateral distance; at pedestrian crossings, (cf. pos. 38, 39)

23 Mistakes made when being overtaken

Driving past

24 Failure to observe the priority of oncoming cars when driving past stationary vehicles, barriers or obstacles (§ 6) (except pos. 32)

25 Failure to observe the rear traffic when driving past stationary vehicles, barriers or obstacles and/or without timely and clearly indicating the intention to swerve out

Driving side by side

26 Incorrectly changing the lane when driving side by side or failure to observe the "zip method" (merging of two queues with alternate priority of the respective cars (§ 7) (except pos. 20, 25)

Priority, precedence

27 Failure to observe the rule "right has priority over left"

28 Failure to observe the traffic signs regulating the priority (§ 8) (except pos. 29)

29 Failure to observe the priority of the passing traffic on motorways or motor vehicle roads (§ 18, para. 3)

30 Failure to observe the priority by vehicles coming from dirt roads

31 Failure to observe the traffic control by policemen or traffic lights (except pos. 39)

32 Failure to observe the priority of oncoming vehicles (traffic sign No. 208 of Road Traffic Regulations)

33 Failure to observe the priority of rail vehicles at railway crossings

Turning, U-turn, reversing, entering the flow of traffic, starting off the edge of the road

35 Mistakes made when turning (§ 9) (except pos. 33, 40)

36 Mistakes made when making U-turn or reversing

37 Mistakes made when entering the flow of traffic (e.g. from premises, from another part of the road or when starting off the edge of the road)

Improper behaviour towards pedestrians

38 at pedestrian crossings

39 at central islands

40 when turning

41 at stops (also at school busses stopping with the warning flasher device flashing)

42 at other places

Stationary vehicles, safety measures

43 Unlawful stopping or parking

44 Insufficient safety measures in the case of vehicles stopping or broken down and accident sites or with regard to school busses with children getting on or off the bus

45 Behaviour contrary to traffic regulations when getting on or off a vehicle, loading or unloading

46 Failure to observe lighting regulations (except pos. 50)

Load, number of passengers

47 Overload, maximum number of passengers exceeded

48 Insufficient safety measures with regard to load or vehicle accessories

49 Other mistakes made by driver

Technical or maintenance faults:

50 Lighting

51 Tyres

52 Brakes

53 Steering mechanism

54 Towing equipment

55 Other faults

Improper behaviour of pedestrians:

Improper behaviour when crossing the carriageway

60 at places where the pedestrian traffic was controlled by policemen or traffic lights

61 on pedestrian crossings without control by policemen or traffic lights

62 near junctions, traffic lights or pedestrian crossings with heavy traffic at other places:

63 by suddenly emerging from behind obstacles obstructing the visibility

64 without paying attention to the traffic

65 by other improper behaviour

66 Failure to use footway

67 Failure to use proper side of the road

68 Playing on or near carriageway

69 Other improper behaviour of pedestrians

General causes:

Road surface conditions

Slippery carriageway

70 Impurity through oil leakage

71 Other impurities caused by road users

72 Snow, ice

73 Rain

74 Other influences (among others, leaves, loam washed up)

Road condition

75 Grooves in connection with rain, snow or ice

76 Other road condition

77 Irregular condition of traffic signs or installations

78 Insufficient road lighting

79 Insufficiently secured railway crossings

Influence of the weather

Obstruction of visibility by

80 Fog

81 Heavy rain, hail, flurry of snow and the like

82 Dazzling sunshine

83 Side wind

84 Storm or other weather influences

Obstacles

85 Road construction site on carriageway not or not sufficiently secured

86 Wild animals on the carriageway

87 Other animal on the carriageway

88 Other obstacle on the carriageway (except pos. 43, 44)

89 Other causes (list and briefly describe)

Appendix 3.2

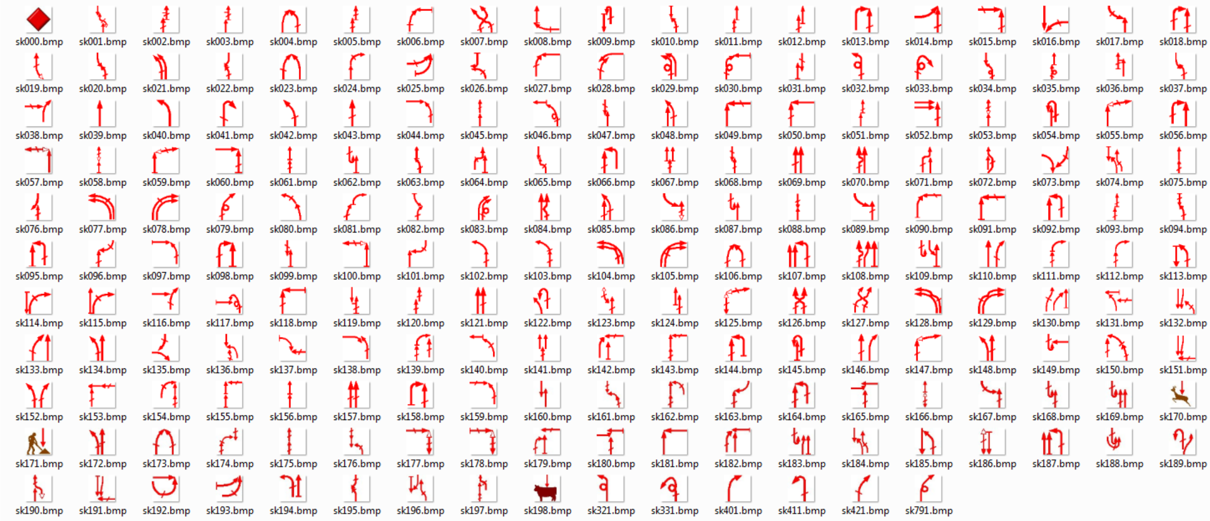


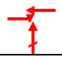
Figure A.1 The 205 symbols used in the Belrin police-reported accident database.

The meanings of components in the accident symbols that are used by the Berlin police are as follows:

-  Generally, an arrow represents a road user involved accidents. It could be a motorized vehicle, a bicycle and a pedestrian (thereafter a vehicle is collectively used.)
-  An arrow marked with a crossing line represents a vehicle that is responsible for the accident.
- The arrow direcitons represent the movement directions of the vehicles, while the directions of the starting part of arrows state where the vehicles comes from. For example,  represents vehicles that turn left;  represents vehicles that go trough;  represents vehicles that turn right;  represents vehicles that turn around.
-  represents parked (responsible) vehicles.
-  represents vehicles that keep stay due to requirements of the traffic.
-  represents vehicles that back up (and are responsible for accidents).
-  represents vehicles that change lanes or making the zipper merge (and are responsible for accidents).
-  represents vehicles that are running at inappropriate speed (and are responsible for the accident).
-  represents accidents at construction sites.
-  and  represent accidents with animals.

Appendix 3.3

Table A.1 Symbols involving the cross traffic in police-recorded accidents; the numbers of accidents that each symbol corresponded to and the accident causation.

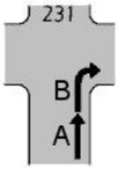
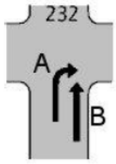
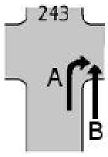
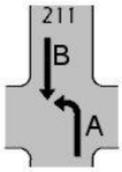
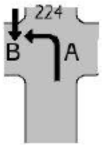
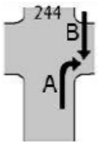
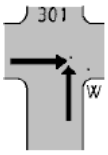
Symbols	Symbol Nr.	Accident number	Causation				
			Cause Nr. 35* by bicycles	Cause Nr. 35 by cars	Cause Nr. 37** by bicycles	Cause Nr. 37 by cars	Others
	6	14	1	0	1	0	12
	8	14	0	0	0	0	14
	14	23	11	5	2	1	4
	15	353	3	170	10	51	119
	16	18	3	1	6	2	6
	27	19	1	2	3	0	13
	28	5	0	0	0	0	5
	30	0	0	0	0	0	0
	38	5	1	1	1	0	2
	44	20	2	2	3	1	12
	49	1187	328	175	465	41	178
	50	1276	562	181	372	7	154
	52	4	3	0	1	0	0
	60	1	0	0	0	0	1
	73	1	0	0	0	0	1
	90	4	0	0	0	0	4
	91	66	1	0	3	0	62
	97	4	0	0	0	0	4
	116	19	3	3	1	0	12
	118	25	0	1	0	0	24
	135	1	0	0	1	0	0
	138	0	0	0	0	0	0
	140	2	0	0	0	0	2
	142	1	0	0	1	0	0
	143	60	27	0	29	0	4
	151	2	2	0	0	0	0
	153	27	19	0	8	0	0
	155	1	1	0	0	0	0
	159	1	1	0	0	0	0
	165	1	1	0	0	0	0
Total		3154	970	541	907	103	633
Ratio		1	0.31	0.17	0.29	0.03	0.20

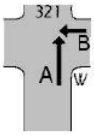
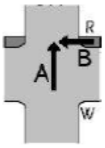
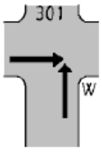
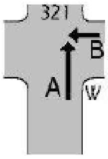
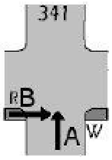
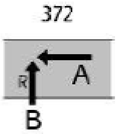
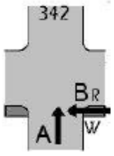
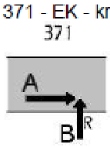
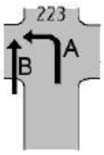
* Cause Nr. 35: Red-light-violation

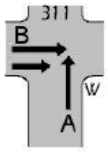
** Cause Nr. 37: Mistakes made when entering the flow of traffic

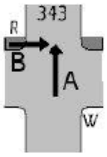
Appendix 3.4

Table A.2 GIDAS accident (2005-2013) classification into different scenarios according to the type of accidents.

Scenarios	Types of accident (Nr., motion and diagram)	Accident numbers
R20	231 - AB - Rechtsabb. u. Nachfolgender hintereinander  232 - AB - Rechtsabb. u. Nachfolgender nebeneinander  243 - AB - Rechtssabb. u. Radf. Radweg gleiche Richtung 	91
L12	211 - AB - Linksabb. u. Gegenverkehr geradeaus  224 - AB - Linksabb. u. Radf. vom Radweg Gegenrichtung 	69
R17	244 - AB - Rechtssabb. u. Radf. vom Radweg Gegenrichtung 	61
T11	301 - EK - Bevorrechtigter von links, Wartepflichtiger geradeaus  321 - EK - Bevorrechtigter von rechts u. geradeaus	53

	 344 - EK - Bevorrechtigter Radf. vom Radweg von rechts Gegenseite u. geradeaus  	
T16	301 - EK - Bevorrechtigter von links, Wartepflichtiger geradeaus  321 - EK - Bevorrechtigter von rechts u. geradeaus  341 - EK - Bevorrechtigter Radf. vom Radweg von links u. geradeaus  372 - EK - kreuz. einfahr. Radf. von links  	52
T13	342 - EK - Bevorrechtigter Radf. vom Radweg von rechts u. geradeaus  371 - EK - kreuz. einfahr. Radf. von rechts  	50
L9	223 - AB - Linksabb. u. Radf. Radweg gleiche Richtung  	20
T18	311 - EK - Bevorrechtigter Überholer von links u. geradeaus	13

<table>
<tr><td></td><td>

343 - EK - Bevorrechtigter Radf. vom Radweg von links Gegenseite u. geradeaus

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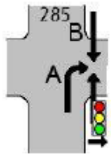
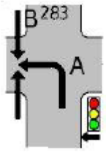
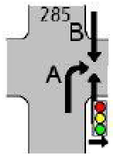
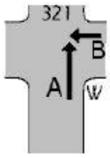
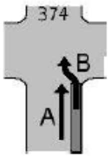


283 - AB - Linksabb. mit Pfeillichtzeichen u. Radf. auf Radweg


285 - AB - Rechtsabb. mit Pfeillichtzeichen u. Radf. auf Radweg


321 - EK - Bevorrechtigter von rechts u. geradeaus


349 - EK - Bevorrechtigter Radf. vom Radweg Sraßenseite, Richtung unklar
349
Straßenseite
Fahrt-
richtung
von R unklar
399: Sonstige Einbiegen/Kreuzen-Unfälle</td><td>13</td></tr>
<tr><td>T20</td><td>374 - EK - kreuz. einfahr. Radf. an Knoten

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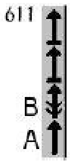
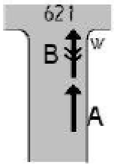
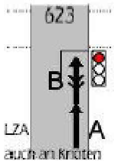
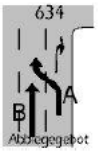
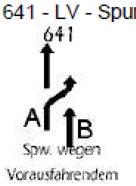
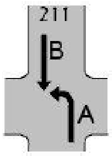
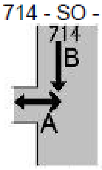
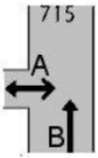
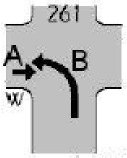
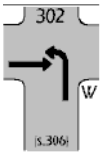
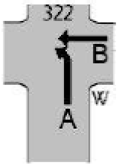
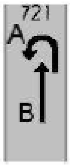
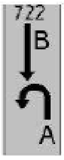
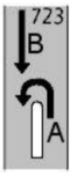
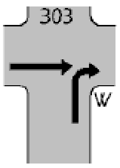
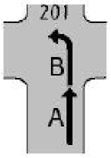
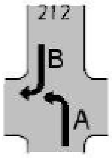
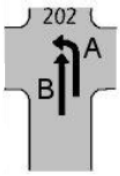
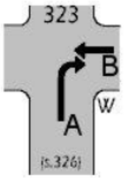
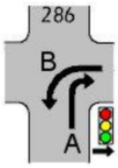
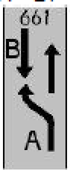
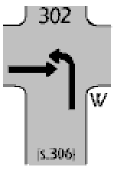
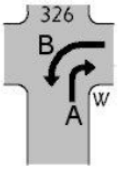
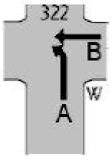
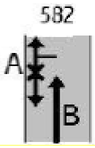
	611 - LV - Stau u. Nachfolgender erste Spur  621 - LV - Wartepflichtiger u. Nachfolgender  623 - LV - Wartepflichtiger u. Nachfolgender vor Knoten, LZA  634 - LV - Spurwechsler nach links wg. Abbiegegebot u. Nachfolgender  641 - LV - Spurwechsler nach rechts wg. Vorausfahrenden u. Nachfolgender  651 - LV - Nebeneinanderfahrende gleiche Richtungsfahrbahnen 	
T15	211 - AB - Linksabb. u. Gegenverkehr geradeaus 	6
Collision concerning baking up	712 - SO - Rückwärtsrollen  714 - SO - rückwärtsausfahren rechts 	5

	715 - SO - rückwärtsausfahren links 	
L16	261 - AB - Linksabb. u. Wartepflichtiger  302 - EK - Bevorrechtigter von links, Wartepflichtiger nach links 	3
T19	322 - EK - Bevorrechtigter von rechts u. linkseinbieger 	3
Collision concerning turning over	721 - SO - Wenden u. Nachfolgender  722 - SO - Wenden u. Gegenverkehr  723 - SO - Wenden u. Gegenverkehr nach Verkehrsinsel 	3
R16	303 - EK - Bevorrechtigter von links, Wartepflichtiger nach rechts 	2

L20	201 - AB - Linksabb. u. Nachfolgender hintereinander 	2
L1	212 - AB - Linksabb. u. Gegenverkehr rechtsabb. 	2
T10	202 - AB - Linksabb. u. Nachfolgender nebeneinander  203 - AB - Linksabb. u. Nachfolgender Radf. vom Radweg 	2
R11	323 - EK - Bevorrechtigter von rechts u. rechtseinbiegen 	1
R14	286 - AB - Rechtsabb. mit Pfeillichtzeichen u. Linksabbieger 	1
T12	661 - LV - Überholer Gegenverkehr 	1
T14	302 - EK - Bevorrechtigter von links, Wartepflichtiger nach links 	1

L3	326 - EK - Bevorrechtigter von rechts u. abbiegend linksabbiegen 	1
L11	322 - EK - Bevorrechtigter von rechts u. linkseinbiegen 	1
Collision concerning stationary traffic	582 - RV - Tür öffnen beim Ein- oder Aussteigen (linker Fahrbahnrand) 	1

Appendix 4.1

Table A.3 Detected safety-critical events based on a deceleration trigger

Participant Nr.	Number of critical events (<= -0.4 g)	Deceleration values (g)	Event description
1	2	0.48; 0.41	1. Decelerated for right-turning; 2. Braked on red light at a signalized intersection.
2	3	0.48; 0.41; 0.40	1. Caused by noises; 2. Caused by noises; 3. Caused by noises.
3	1	0.46	1. Decelerated for right-turning.
4	3	0.43; 0.51; 0.70	1. Braked to yield to a bicycle from a refuge island; 2. Caused by noises; 3. Decelerated for left-turning.
5	2	0.52; 0.57	1. Caused by (zero-) noises; 2. Braked due to a car from the right that did not follow the yield sign.
6	2	0.45; 0.44	1. Decelerated in changing the lane for left-turning; 2. Decelerated in approaching a yield-sign intersection.
7	4	0.43; 0.44; 0.41; 0.43	1. Caused by noises; 2. Braked in approaching a no-sign intersection to yield to the crossing pedestrians; 3. Braked before right-turning at a signalized intersection to yield to a through bicycle; 4. Decelerated for left-turning.
8	1	0.44	1. Caused by noises.
9	4	0.45; 0.42; 0.54; 1.60	1. Braked for left-turning; 2. Decelerated in changing the lane; 3. Braked on red light at a signalized intersection; 4. Caused by (zero-) noises.
10	0	\	\
11	0	\	\
12	0	\	\
13	1	0.43	1. Braked in approaching a yield-sign intersection.
14	1	0.65	1. Caused by noises.
15	0	\	\
16	0	\	\
17	0	\	\

18	0	\	\
19	2	0.42; 0.41	1. Decelerated by passing a car on a narrow road; 2. Braked to yield to a car from the right at a no-sign intersection.
20	1	0.52	1. Caused by noises.
21	0	\	\
22	0	\	\

Appendix 4.2

Events corresponding to outliers in the box plots of bicycle-scanning strategies.

Outlier(s) in Figure 4-11

Outlier 1 in the period of "turning": The traffic light turned green and the bicycle started from still, when the car was approaching the intersection. Therefore, the bicycles were still crossing the intersection and the car driver had to observe the bicycles, when the car arrived at the intersection and started turning. Actually, this event could be also classified in R20_3.

Outliers in Figure 4-12

For R20_2:

Outlier 2 in "Waiting-at-red" period: In waiting-at-red period, the car driver had few driving tasks and just fixated on bicycles, or the red period lasted longer.

Outlier 10 in "Turning" period: There was a (large) truck ahead of the car, and therefore there was certain of distance from the car to the intersection. The time that the car took to go from the stop location to the intersection (after the light turned green) was considered as the turning period. It lasted longer than when the car stopped directly in front of stop line, and thus the car driver took more fixations on bicycles.

Outlier 7 by "Mirror check": This event involved six bikes. It was a combination of type R20_2 and R20_4. Only one bicycle was approaching together with the car (R20_2). After the car arrived at the intersection and stopped at red, the car driver fixated on the other coming bicycles by mirror checks (R20_4). Therefore, it took longer time for fixation by mirror check.

For R20_4:

Outlier 5 in "Approaching" period: The car driver observed the situation at the intersection as well as the bicycle in approaching. Normally, the car driver takes more time to observe the intersection rather than the bicycle, when the bicycle is approaching in a high speed along the road. However, the bicycle was going at a relatively lower speed in approaching the intersection. Therefore, the car driver made more fixations on the bicycle.

Outlier 8 in "Waiting-at-red" period: In waiting-at-red period, the car driver had few driving tasks and just fixated on bicycles, or the red period lasted longer.

Outlier 4 by "Mirror check": The car passed by the bicycle in approaching. After the car arrived at intersection and stopped at red, the car driver checked the side view mirror to observe the coming bicycle. In this case, the mirror check was unnecessary for the safe driving. Normally car drivers would not have made mirror checks.

Outlier 9 by "Mirror check": The same as the above.

For R20_5:

Outlier 8 in "Waiting-at-red" period: In waiting-at-red period, the car driver had few driving tasks and just fixated on bicycles, or the red period lasted longer.

Outlier 9 in "Waiting-at-red" period : The same as the above.

Outlier 21 in "Waiting-at-red" period: The same as the above.

Outlier 30 in "Waiting-at-red" period: The same as the above.

Outlier 3 in "Turning" period: The car driver had to wait to yield to bicycles in motion 17, had few driving tasks and just fixated on bicycles in motion 20 who, however, had already left the crossing route of the car.

Outlier 24 in "Turning" period: The bicycle just arrived at the intersection and was not ready for starting, when the traffic light turned green. Normally, bicyclists would have stated immediately after the traffic light turned green. The car driver took longer to observe the bicyclist, because he had to give the right of way to the bicycle.

Outlier 5 by "Shoulder check": The car driver made shoulder checks to observe actively bicycles coming behind in waiting-at-red period. Normally, the shoulder checks were unnecessary for the safe driving, since the bicycles would come in the forward field of view of the car drivers.

Outlier 11 by "Shoulder check": The same as the above.

Outlier 32 by "Shoulder check": The same as the above.

Outlier 17 by "Shoulder check": After the traffic light turned green, the car started at the same time as bicycles. Normally, no shoulder checks were necessary, because the bicycles were clearly presented in the forward field of view of the car driver. However, since there were more than one bicycle and some were located behind the car driver, the car driver took shoulder checks to observe them. The shoulder checks occurred in turning period.

Outlier 1 by "Mirror check": The car driver made mirror checks to observe actively bicycles coming behind in waiting-at-red period. Normally, the mirror checks were unnecessary for the safe driving, since the bicycles would come in the forward field of view of the car drivers.

Outlier 5 by "Mirror check": The same as the above.

Outlier 18 by "Mirror check": The same as the above.

Outlier 23 by "Mirror check": The same as the above.

Outlier 30 by "Mirror check": The same as the above.

Outlier 32 by "Mirror check": The same as the above.

Outliers in Figure 4-13

For sub-situation 1:

Outlier 19 in "Turning" period: This event concerned a conflict. The bicycle was hidden behind the parked cars, and therefore was no detected by the car driver until the turning period. The car driver was driving the car at a high speed when he detected the bicycle and had to conduct hard brake, and therefore fixated longer on the bicycle in turning.

Outlier 20 in "Turning" period Turning: When the car detected the bicycle in approaching, the bicycles just started because the traffic light turned green from red. The bicycles rode at a relatively lower speed and took longer to cross the intersection. Thus, the car driver fixated longer on bicycles. Normally (in this sub-situation), the bicycle would cross the intersection constantly at a relatively higher speed.

For sub-situation 2:

Outlier 11 in "Approaching" period: There were three cars in front of the subject car. They were going at a slow speed, because the traffic light just turned green from red. Therefore, the car approached the intersection at a relatively lower speed. In addition, the bicycle was riding in parallel with the car and sharing the traffic lane with the car. Thus, the car had to observe the bicycle in the whole approaching period.

Outlier 10 in "Turning" period: The car driver detected bicycles in approaching period and passed by them. After arriving at the intersection, the car driver just waited and observed the bicycles after they came in his forward field of view, and therefore fixated longer on bicycles in turning. Normally, the car driver would have conducted shoulder or mirror checks to observe the bicycles.

Outliers in Figure 4-14

Outlier 18 in "Turning" period: This event concerned a conflict. In approaching, the bicycle was not detected by the car driver, because the bicycle came from the right road. The car had to conduct hard brake to avoid a conflict with the bicycle, and fixated longer on the bicycle.

Outlier 20 in "Turning" period: In front of the subject car, there was another car that also yielded to the bicycle. The car driver had to take longer to wait and fixate on the bicycle in turning period.