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Analysis of cyclists' safety on "bicycle streets" and other facilities in four large Dutch municipalities: A crash and conflict study

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Abstract

In the past two decades the number of bicycle streets in the Netherlands has increased significantly. A bicycle street is a street on which a minimum of two functions are combined; a flow function for bicycle traffic, and an exchange function for motor vehicle traffic. They provide a space efficient solution for facilitating high bicycle flows, while also allowing low volumes of motor vehicles. However, the effects on safety of this sharing of road space compared to more traditional bicycle facilities are unknown. Furthermore, knowledge on (unsafe) road user interactions and behaviour, and how this relates to street design is limited. Therefore, this study aims to provide insight into bicycle street safety through 1) a road segment based crash cost rate analysis using historic crash data; and 2) a supporting conflict study on four bicycle streets.

Crash cost rates for each road segment are calculated for four time periods based on the amount of crashes on a link, the exposure at the time interval, the link length, and the social costs of the crash depending on the severity level (property damage only, light injury, and severe injury/fatal crash). The average rates are tested for significant differences between bicycle streets and other bicycle facilities (bicycle lane, bicycle path, residential roads without bicycle facilities). Tobit regression models are developed using resampled data to quantify the relationships between crash cost rates on bicycle facilities and various traffic, demographic and socio-economic variables. To overcome the issue of limited number of bicycle street and the non-event nature of crash data, the minority group (bicycle streets) is over-sampled using the ADASYN method (Adaptive Synthetic Sampling Approach for Imbalanced Learning).

The conflict study on bicycle streets supports the crash cost analysis by providing in depth understanding of how and why crashes on bicycle streets occur. In the conflict study event characteristics (severity, interaction type, road users, evasive action, design) of safe and conflicting interactions are collected on four bicycle streets that vary in traffic volumes and road profile. Conflict frequencies and conflict rates are analysed for patterns with variables such as bicycle street design, interaction types, and traffic volumes.

This study shows that average crash cost rates on bicycle streets are comparable with the rates on bicycle lanes, and higher than those on bicycle paths and regular residential roads. In addition, the regression models show that cyclists on bicycle streets are exposed to higher risks than on other bicycle facilities when accounting for external variables. Both the crash cost rate analysis and conflict study produced similar results on the effects of bicycle volumes on crash and conflict rates. Namely, increased bicycle volumes are related to increased crash and conflict rates on bicycle streets. Duo-cyclists are exposed to the highest conflict rates, and are strongly disadvantaged on narrow and/or high volume bicycle streets. Motor vehicles are frequently involved in conflicts, but relations with traffic safety are uncertain. However, based on the conflict study results, it is suspected that bicycle streets with very low motor vehicle volumes do not properly facilitate interactions with motor vehicles, as they are primarily designed to facilitate interactions between cyclists.

It should be noted that the results are subject to limitations in the crash and traffic volume data. However, the high crash cost rates on bicycle streets clearly highlight the need for a better understanding of road user interactions and behaviour, and the role of street design and traffic on bicycle street safety. The conflict study provides first insights into this, and topics for future research directions.

Key words: Bicycle street, safety, crash cost rate, Tobit regression, conflicts

1 Introduction

Starting in the 2000s, a new type of bicycle infrastructure, the *fietsstraat* (bicycle street) emerged and its numbers are rapidly increasing. A bicycle street is a street on which (minimum) of two functions are combined; a flow function for bicycle traffic and an exchange function for motor vehicle traffic (Andriesse & Ligtermoet, 2005). The main benefit of bicycle streets is that they are a space-efficient way to facilitate large flows of cyclist, while also allowing local access for motor vehicles. These streets can for example serve as the missing link on a main cycling route, where there is no room for a separate bicycle facility.

However, since the bicycle street is not a legalized facility, for which engineers must comply with design regulations, various bicycle street designs exist. Road profiles differ in width, pavement, and the implementation of rabat strips and a median (Andriesse & van Boggelen, 2016). As a response, recommendations for the implementation (or non-implementation) and design were recently published to aid municipalities and engineers in where and how to implement bicycle streets for optimal performance, in terms of minimal conflicts and road user experience (Godefrooij & Hulshof, 2017; van Boggelen & Hulshof, 2019). These guidelines were based on perceived safety and conflict studies on bicycle streets, but do not address the impact of the streets' effect on cyclists' safety within the bicycle network.

Generally, separating cyclists from motor vehicles is beneficial to cyclists' safety (van Petegem, Schepers, & Wijlhuizen, 2021). Furthermore, increased motor vehicle volumes and driving speeds are associated with a reduction in bicycle safety (Chen & Shen, Built environmnet effects on cyclist injury severity in automobile-involved bicycle crashes, 2016; Uijtdewilligen, et al., 2022). Bicycle streets, in theory, counteract these negative effects by placing the cyclists in a more dominant position on the road through design (i.e. the rabat strip) (Andriesse & Ligtermoet, 2005). However, what is the effect of this on cyclists' safety, opposed to facilitating them with separate lanes or paths? Furthermore, no studies have been performed to address whether this dominance strategy has the desired effects. This leaves to wonder: how do cyclists and motor vehicles interact on bicycle streets, is motor vehicle traffic indeed calmed through design, do motor vehicles adapt their speeds and behaviour, and how does this differ between the variety of bicycle street designs?

These are all relevant questions on the performance of bicycle streets in terms of safety for cyclists. To address this knowledge gap this study aims to provide insight into the safety of bicycle streets, through a comparison of crash cost rates on bicycle streets and other bicycle facilities, and a conflict study on bicycle streets to more specifically address the characteristics of (interaction types, involved road users, driving speed), and related factors to (design, traffic volumes), unsafe interactions. Thus, both the safety of bicycle streets as well as the background of how and why unsafe events occur is addressed.

2 Background

This chapter addresses main factors associated with cyclists' safety on the bicycle network, and on bicycle streets specifically. The effects of these factors on different safety metrics are summarized in figure 1, and further elaborated in this chapters' sub-sections (2.1 Cyclists' safety and 2.2 Bicycle street safety).

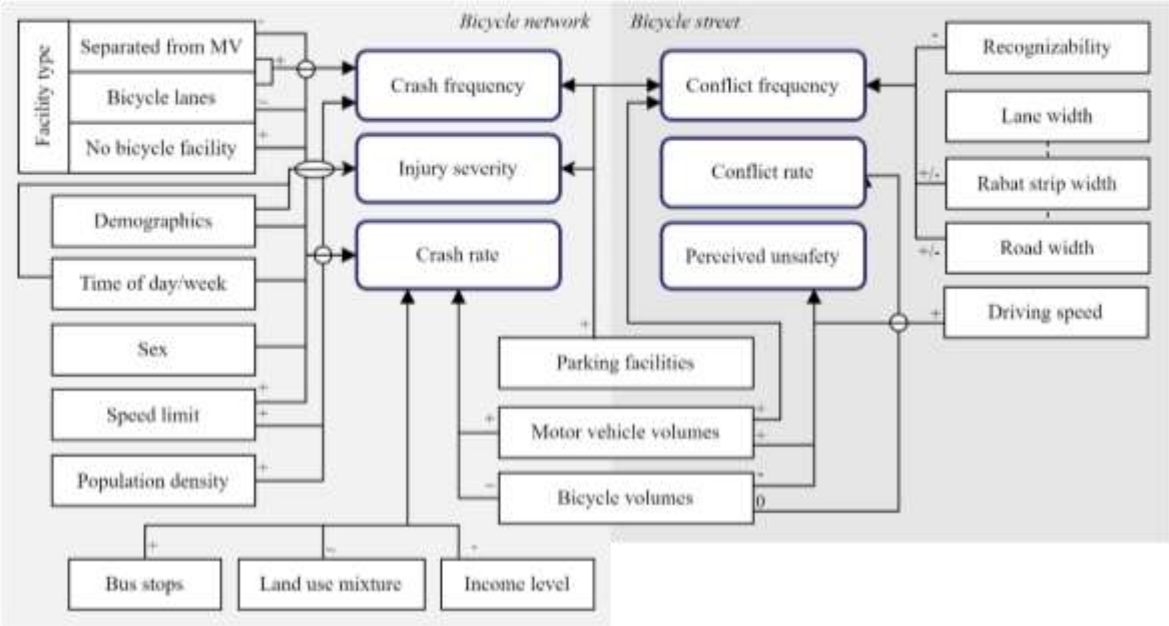


Figure 1 Flow-chart summary of the effects of crash, traffic, and environmental variables on bicycle safety indicators on bicycle facilities and specifically bicycle streets

2.1 Cyclists' safety

A variety of infrastructure, traffic, temporal, built environment, socio-economic, and demographic factors are associated with cyclists' safety. Table 1 summarizes the main effect of these factors on cyclists' safety in terms of crash frequency, crash rate, and/or injury severity.

Significant differences in the safety of bicycle facilities (bicycle paths, lanes and absence of facility) and crash locations (intersection versus street segment) are found. Where the majority of crashes occur at intersections. Overall, separated bicycle facilities are found to be safest, and the absence of a bicycle facility is related to increased crashes. This is in line with the idea that homogeneity on a street benefits safety. The literature is inconsistent on the safety of bicycle lanes as this strongly depends on the type of comparison and site-specific conditions.

Before-after studies that find an increase in crashes on new bicycle facilities often also observe an increase in bicycle volumes. Indicating that when evaluating the effect of new facilities, crash rates are a better metric than crash frequency. Furthermore, on an area level, higher bicycle volumes are associated with reduced crash rates, while the total crash count is likely to be higher.

Motor vehicle volumes are also relevant to cyclists' safety. Uijtdewilligen et al. (2022) found that, in a case study of the city of Utrecht, increasing exposure to motorised vehicles increases the number of bicycle crashes on 50 km/h roads. However, no significant differences were found at 30 km/h roads. On the other hand, it is presumable that on 30 km/h roads with mixed traffic conditions motor vehicle volumes also relate to bicycle crash rates. For example, as described in the next section, bicycle and motor vehicle volumes are main predictors of the performance of bicycle streets.

Next, the literature shows that crash-related factors such as age, sex and time of the collision are significant predictors for crashes, where older people and men are at higher risk. Daily variations in crash rates between rush and non-rush hours are often not included as traffic data is limited to annual averages. However, it is presumable that the number of crashes per cyclist fluctuates between high and low traffic volume periods. Studies are conclusive on the fact that those traveling in the dark are at higher risk of a crash.

Road design and built environment factors, such as road width, speed limit, roadside parking, and bus stops, are associated with crash rates. However, the effect of land use mixture on crash rates is uncertain. Lastly, high population density is associated with more meetings between road users and thus, more crashes. Research on the relationship between crash rates and socio-economic factors is limited, but one study showed that income level is negatively associated with crash frequency, while controlling for traffic volumes.

2.2 Bicycle street safety

Due to the novelty of bicycle streets and its small numbers, studies on bicycle street safety are sparse. These studies address bicycle street safety in terms of perceived safety from a motorist and/or cyclist perspective (Khut, 2012; Denvall & Johansson, 2013; Olsson & Elldér, 2023), conflict frequencies and user behaviour (Delbressine, 2013; Godefrooij & Hulshof, 2017), or both (van Boggelen & Hulshof, 2019).

Perceived safety studies generally conclude that lowering motor vehicle volumes and driving speeds have positive effects on cyclist experiences. Furthermore, duo cyclists are found to have a more negative experience on narrow bicycle streets.

Delbressine (2013) and Godefrooij & Hulshof (2017) both conducted a conflict study on Dutch bicycle streets. The former aimed to conclude on bicycle street safety by linking conflict observations with the Sustainable Safety principles (SWOV, 2018). It was concluded that the homogeneity of the streets is poor as motor vehicles do not adhere to speed limits. Also, road user behaviour was found to be unpredictable due to the lack of recognizability of the various designs. Overall, the contradicting functions were concluded to be the source of high conflict numbers. For example, parking in the street created dangerous obstacles for through cycling cyclists, however this is implicit for the access function for motor vehicles.

The latter conflict study served as a base for van Boggelen & Hulshof (2019), who summarized the relationship between bicycle street performance and street characteristics, including vehicle intensities, road width, and rabat strip width. The performance is measured in terms of a grade (1-10) based on user experiences. An increase in motor vehicles results in a lower performance grade, while cyclists are positively associated with performance. Traffic reducing measures, such as eliminating of restricting motor vehicles from certain directions, may help to maintain low volumes or reduce volumes, and serves as a very effective measure for reducing the number of bothersome and/or dangerous encounters (CROW Fietsberaad, 2021). Van Boggelen & Hulshof (2019) also found a negative exponential relationship between the total road width minus the rabat strip width and the performance grade. In other words, the number of bothersome/dangerous encounters increases rapidly when the road width is insufficient for evasive manoeuvres. On the other hand, experiences on bicycle streets in Münster (Germany) showed that a too wide roadway (over 5 meters) results in increased motor vehicle speeds (Schroeder, 2021). Similarly, Delbressine (2013) observed generally lower speeds on narrow bicycle streets as motor vehicles were forced to stay behind cyclists. Thus, an optimum road profile exists which provides sufficient space for encounters while maintaining low speeds.

Table 1 Overview factors associated with cyclists' safety

Factor		Crash rate association	Association with cyclists' safety	Source
Crash related factors				
Location	Street section	Significant differences in safety of bicycle facilities at intersections versus street segments.	+	Hull & O'Holleran (2014)
	Intersection	Majority of bicycle crashes occur on intersections.	-	Garder et al. (1994); Schepers et al. (2013)
Cyclist	Age	Compared to car travel, cycling is found to be riskier for all age groups, except 20-29 years old. Older or elderly cyclists are associated with increased injury risk.	Elderly: -	Wegman et al. (2012). Vanparijs et al. (2015); Chen & Shen (2016); Chimba & Musinguzi (2016).
	Sex	Overall a higher accident rate found for men.	Men: -	Vanparijs et al. (2015)
Temporal	Time of day	Both the risk of collision and crash severity increases in the dark.	Dark: -	Vanparijs et al. (2015); Chimba & Musinguzi (2016).
	Day in week	Cycling risk is found to particularly high in the weekends between midnight and 6 in the morning.	Weekend: -	Dozza (2017).
Traffic, roadway and other factors				
Traffic volume	Bicycle volume	A small increase in the number of fatalities with an increase of bicycle modal share.	-	Schipdonk & Reurings (2012).
		No significant change in fatalities with increased bicycle share.	0	Schepers & Heinen (2013).
		Large spatial differences in the effects of bicycle share on fatality risk.	0	Vandenbulcke et al. (2009).
		Positive effects on bicycle safety observed when increased/high bicycle modal share.	+	Schepers et (2017) al.; Wegman et al. (2012).
		Positive relationship between PDO, severe, and fatal crash frequencies and bicycle volumes.	-	Asadi et al. (2022).
		'Safety in numbers' concept, that drivers are less likely to collide with a cycling person when there are more cyclists present; Due to greater awareness.	+	Jacobsen (2003); Mapes (2009).
		No effect of bicycle volumes on the number of conflicts per cyclist on bicycle street.	0	CROW (2021).
	Motor vehicle volume	Increased volumes related to increased crash rates on 50km/h roads Zones with more motor vehicle trips have more bicycle crashes. Motor vehicle volumes positively associated with severe and fatal bicycle-motor vehicle crashes. The presence of large vehicles, such as vans, large automobiles and trucks, negatively influences bicycle safety. Both the number of cyclists and motor vehicles play a role in BMV crashes. The ratio B/MV traffic is the main predictor for a successful (thus safe) bicycle street.	-	Uijtdewilligen et al. (2022). Chen (2015). Asadi et al. (2022). Chen & Shen (2016). Prati et al. (2018). van Boggelen & Hulshof (2019).
Bicycle facility	Bicycle path	10% increase in crashes and injuries on new bicycle paths (also increase in bicycle volume).	0	Jensen (2007).
		Slight drop in in the number of crashes involving cyclist on street segments after the introduction of cycle tracks.	+	Jensen et al. (2006).

	Bicycle lane	Number of bicycle crashes on cycle lanes is almost double of those occurring on cycle tracks (along distributor roads, at road segments); Cycle lanes do not provide safety benefits over mixed traffic.	- 0	van Petegem et al. (2021).
		New bicycle lanes increased the number of crashes injuries by 5 and 15% respectively.	-	Hoffman et al. (2010); Jensen (2007).
		Bike lanes are associated with a lower risk of collision.	+	Chen, et al. (2021a).
		Bike lanes help increase driver awareness.	+	Sadek et al. (2007).
	Separate facility (i.e. path/ lane)	Bicycle facilities that physically separate cyclists from motor vehicles are the safest bicycle facility type.	+	Winters et a (2012) l.; Lusk et al. (2011); Schepers et al. (2011).
		Unbundling (=separating bicycle and motor vehicle traffic on a network level) improves bicycle safety.	+	Schepers et al. (2013).
	Bicycle street	Bicycle boulevards (similar to bicycle streets) offer safety benefits to cyclists on roads with low traffic volumes and speeds.	+	DiGioia et al. (2017)
	No facility	Absence of bicycle facility associated with increase in BMV crashes.	-	Prati et al. (2018).
Road design	Total road width	Positively associated with the number of conflicts on a bicycle street.	-	CROW (2021).
	Speed limit	Higher driving speeds are associated with higher probabilities of crashes. Areas with low speeds show a decrease of collisions. Reducing vehicle speed is significant in improving cyclist safety.	+	Chen & Shen (2016); Cheng (2015). Lee et al. (2015). Schramm & Rakotonirainy (2009).
	Rabat strip width (BS)	Smaller strip reduces the number of conflicts, with 0.4m as optimum.	Smaller strip: +	CROW (2021).
Built environment	Roadside parking	The presence of road-side parking increases crash likelihood; Prohibited parked cars even more. On-street parking was also found to affect cyclist injury severity.	-	Jensen et al. (2006); van Petegem et al. (2021); Winters et al. (2012). Klassen et al. (2014).
	Bus stop	Collision risk increases with bus stop in close proximity. On area level, high bus stop density associated with more crashes.	-	Prati et al. (2018). Obelheiro et al. (2020).
	MXI	Reduction in crash probability in areas with higher levels of land use diversity.	+	Chen & Shen (2016); Schepers et al. (2019); Asadi et al. (2022).
		Diverse land use (based on a different index) was associated with more injury crashes.	-	Obelheiro et al. (2020).
		Studies have mixed results on the effect of land use mixture on injury severity.	0	Chen & Shen (2016); Zahabi et al. (2011); Yao & Loo (2012).
Demographic	Population density	Associated with an increase in traffic and bicycle crashes. Higher population density results in more frequent interactions between road users and thus increases crash risk. No significant relationship is found between population density and cyclist injury severity.	Increased density: - 0	Clifton & Kreamer-Fults (2007); Park et al. (2015); Lee et al. (2014); Lovegrove & Sayed (2006). Huang, Abdel-Aty, & Darwiche (2010). Zahabi et al. (2011).
	Income level	Negatively associated with crash frequency.	Low IL: -	Asadi et al. (2022).

3 Conceptual framework

Previous studies have shown that cyclists' safety is affected by various factors: traffic conditions (e.g. bicycle and motor vehicle intensities), temporal variations (e.g. day of week, time of day), individual characteristics (e.g. age, gender), built environment (e.g. population density, land use mixture), and road design (e.g. facility type, road profile). Based on these findings, a theoretical framework for bicycle street safety is developed (figure 2). To gain insight into bicycle street safety, by considering all forementioned factors, this study is split into two parts: 1) a comparison of traffic safety, in terms of crash cost rate, on bicycle streets versus other bicycle facilities, and 2) a conflict study for an in depth understanding of how and why near crash events occur.

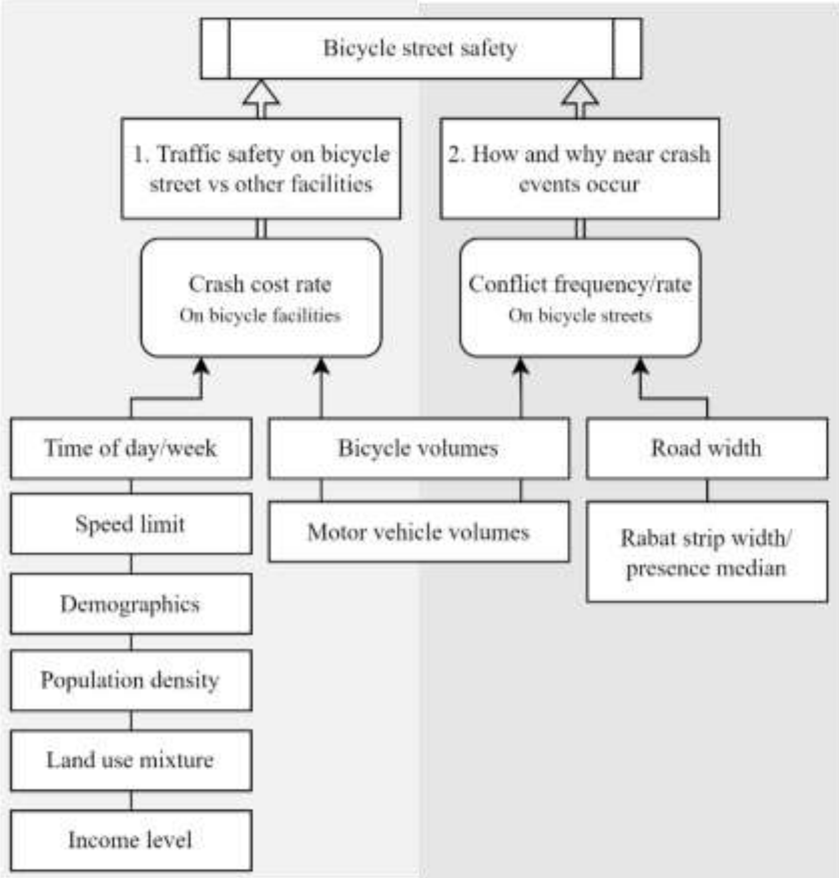


Figure 2 Theoretical framework

For this study three research questions are formulated:

1. How do crash cost rates on bicycle streets compare with bicycle paths, bicycle lanes, and residential roads, at different time periods?

This study adopts a road segment based crash data evaluation. The cyclists' crash cost rate, where a crashes are weighted by the social costs associated with their severity, on all segments of the selected bicycle network is calculated. Traffic exposure is accounted for using model estimates of hourly bicycle volumes. Furthermore, the temporal variation of traffic safety is addressed by analysing crash cost rates over the entire week (average), during rush hours (rush), non-rush hours (non-rush), and weekends (weekend). Finally, average crash cost rates per facility are compared using statistical hypotheses tests.

2. How does the crash cost rate between bicycle streets and other facilities compare when controlling for external factors, and what is the relationship between cyclists' crash cost rate and these factors on different bicycle facilities?

The Tobit regression model is used to understand the relationship between the calculated crash cost rates and external factors, such as traffic volumes, speed limit, built environment characteristics, and socio-economic elements. Multiple models are developed to assess 1) the crash cost differences between bicycle streets and other facilities, by modelling the facilities as categorical variables, and 2) the impact of the external factors on the crash cost rates on each facility, though separate models.

3. How many conflicts occur on the selected bicycle streets, how can they be characterised, and what is their relation to traffic volumes?

One day of video data is collected on each of the four selected bicycle streets that vary in design and traffic volumes. Event characteristics, such as the severity of the interaction, type of interaction, involved road users, road position, driving speed, and any evasive or breaking actions, are noted for each possibly critical interaction. These characteristics provide background how and why near-crash events occur. In addition, conflict frequencies and conflict rates are analysed for patterns with bicycle street design, conflict types, and traffic volumes.

4 Data

In the analysis an extensive variety of data types and sources were used (table 2). This chapter describes the data structure of the bicycle network, crashes, traffic volumes, and environmental factors.

Table 2 Data

Data	Source
Bicycle crashes (location, type, involved road users, time of day & week)	BRON (2016-2021)
Bicycle volumes Motor vehicle volumes	Uijtdewilligen, et al. (2022)
Bicycle facilities (location, type) Speed limit	Dutch Cyclists' Union (2020)
Population density Age group ratio & number of households Median income level	CBS (2020)
MXI	Planbureau voor de Leefomgeving (2022)

4.1 Bicycle network

This study disaggregates between four bicycle facilities: 1) bicycle path, 2) bicycle (suggestion) lane, 3) bicycle street, and 4) no facility roads (i.e. residential 30 km/h road without bicycle facilities). Locations of these facilities are obtained from the Dutch Cyclists' Union (2020) (*Fietsersbond*). The *Fietsersbond* network includes all roads and bicycle facilities in the Netherlands, with a categorisation label of the type of facility.

The labelled bicycle streets in the *Fietsersbond* network were validated based on the following criteria: 1) the street is accessible for both cyclists and motor vehicles, and 2) it has at least one of the following design elements: red pavement, a rabat strip or a central reserve. This ensures wrongly labelled facilities are not included in the study as a bicycle street, and the streets have at least one bicycle street design characteristic. Furthermore, the dataset was updated when bicycle streets were found to be longer, and one bicycle street (Frederiksplein) was added.

Figure 3 Mapped bicycle facilities

4.2 Crash data

This study uses police registered bicycle-involved daytime crashes from the BRON dataset (*Bestand geRegistreerde Ongevallen in Nederland*) between 2016 and 2021 (BRON, 2016-2021). With the exclusion of crashes that occurred on bicycle streets before the bicycle streets were constructed, 12.064 bicycle-involved crashes from 2016-2021 between 7:00-22:00 on both road segments and intersections were included in the study. 101 crashes occurred on bicycle streets (Figure 4). It should be noted that crashes without motor vehicles, and single bicycle crashes are commonly underreported in police registered data sets, including BRON (SWOV, 2017), resulting in underestimation of actual traffic safety levels. Despite these limitations is the BRON dataset still suitable for the aim of this study: comparing traffic safety levels of bicycle streets to other bicycle facilities.

In addition, the crashes were grouped into three severity levels (property damage only (PDO), slight injury, and severe injury/fatality) to create weighted crash rates. Severe and fatal crashes are modelled together as the difference between these severity levels often lies with individual characteristics (e.g. age, gender), road user behaviour (e.g. alcohol, speeding), and temporal characteristics of the crash (Macioszek & Granà, 2022), and this study aims to evaluate the effect of infrastructure. Furthermore, this will prevent fatal crashes from dominating the models.

Figure 5 shows that on bicycle streets more severe/fatal crashes occur compared to other crash severity types, and that these additional severe/fatal crashes occur without motor vehicles present. It should be noted that due to the decreasing registration level with the crash severity (SWOV, 2017), the ratio between crash types in this figure is not comparable. Next, more single-bicycle and bicycle-only crashes are registered on bicycle streets (figure 6). However, 15% of crashes in this study were single-bicycle crashes, while in reality this is estimated to be 60% (Schoon & Blokpoel, 2000). The low ratio of motor vehicle involved crashes is surprising, considering the mixed use function of the facility.

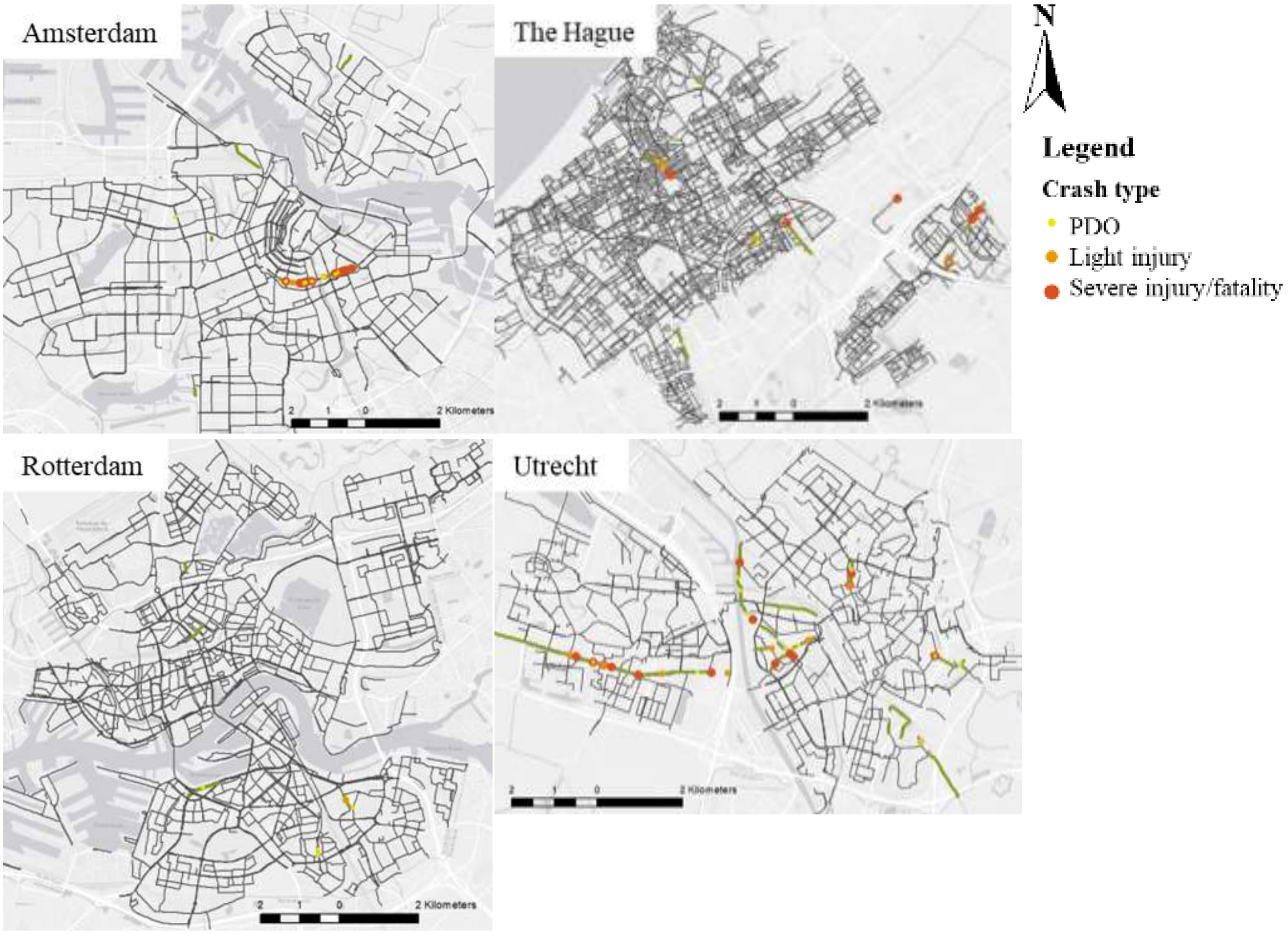


Figure 4 Mapped crashes on bicycle streets in the study network (green)

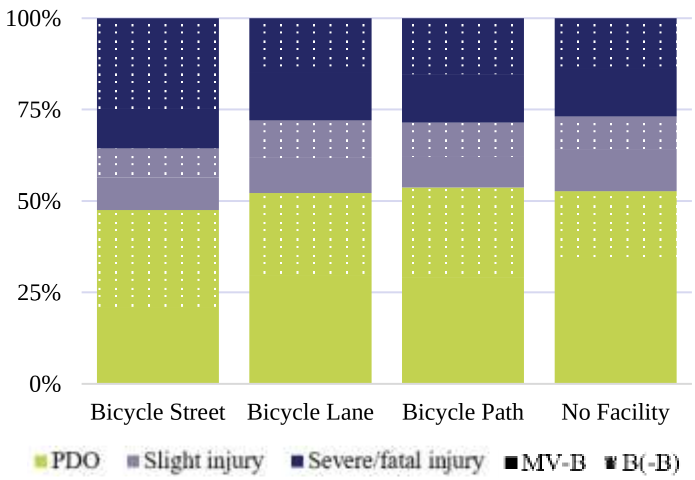


Figure 5 Distribution of crash severities per bicycle facility, disaggregated between motor vehicle involvement yes/no (no is B(-B) and includes B-O, B-B, S-B)

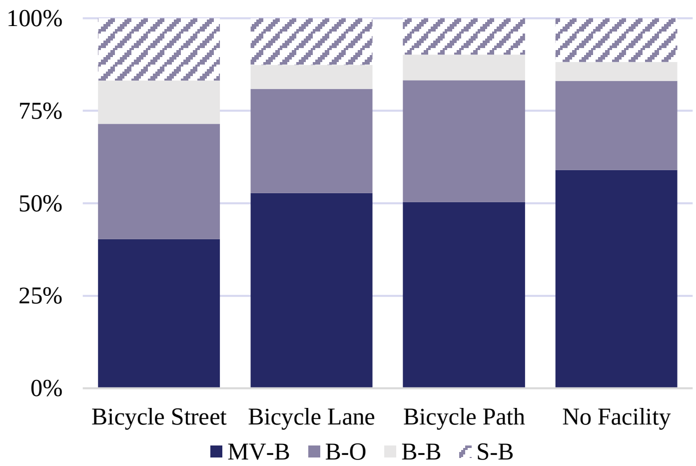


Figure 6 Distribution of crash types per facility. MV = Motor vehicle, B = Bicycle, O = Other, S = Single

The number of crashes per kilometre, i.e. the crash density, is highest on bicycle lanes and paths (figure 7). This is in line with the literature, where the introduction of bicycle facilities is associated with increased bicycle crashes, but also with increase bicycle volumes (Jensen, 2007; Hoffman, Lambert, Peck, & Mayberry, 2010). Crash occurrences on residential roads and bicycle streets are equally low.

Lastly, figure 8 presents the crash densities per municipality and facility. Here, it can be seen that there are strong variations between the municipalities, where the crash densities in Amsterdam are double that of in Utrecht. This variation may be result from differences in crash registration levels between municipalities. Since the ratio's between the facilities within a municipality are comparable between municipalities (e.g. highest density on bicycle lanes), this (possible) variation in crash registration levels is unlikely to effect the aim of this study: comparing safety levels of bicycle facilities.

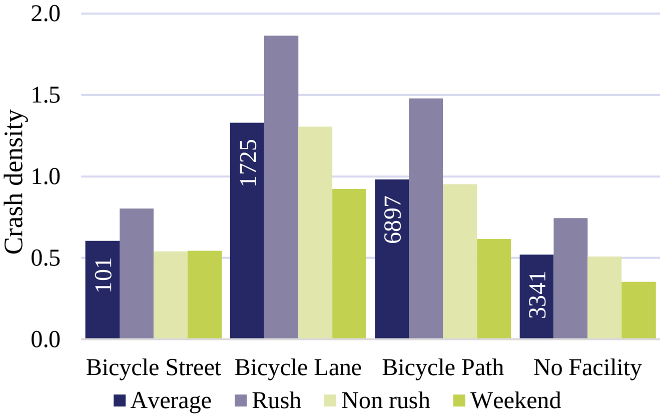


Figure 7 (Annual) crash density per bicycle facility and time period, labelled with total crash counts

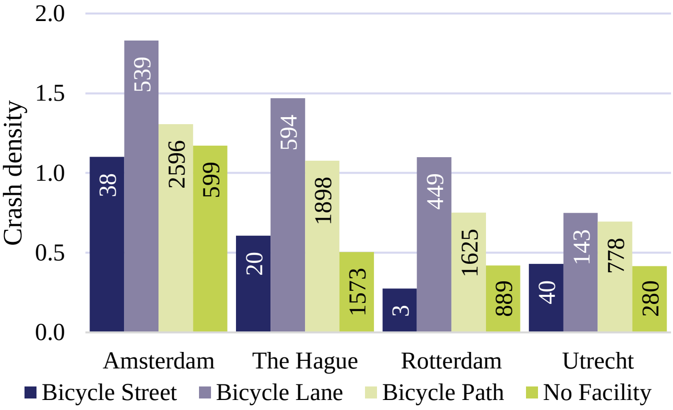


Figure 8 (Annual) crash density per municipality and facility (average time period), labelled with total crash counts

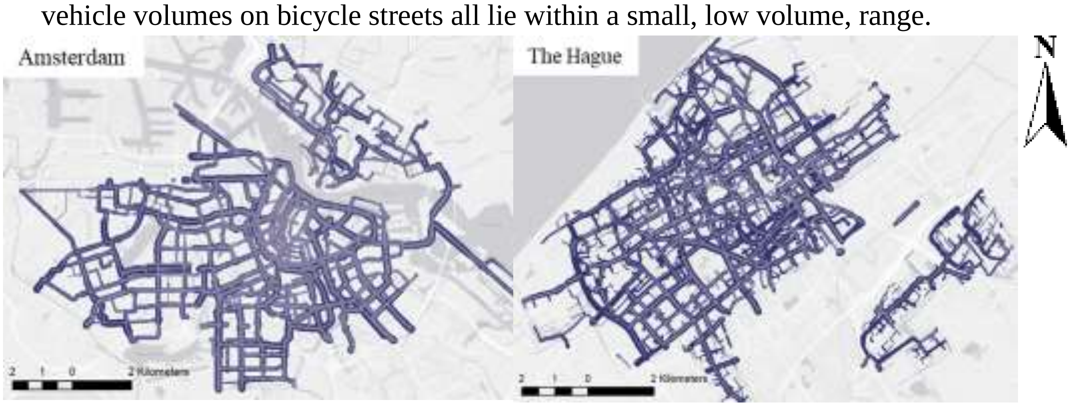
4.3 Traffic volume data

The bicycle and motor vehicle volumes used in this study are obtained from modelled hourly traffic volumes (an extension of Uijtdewilligen, et al. (2022)). The network-wide estimated hourly bicycle volumes are based on two data sets: the Dutch Bicycle Counting Week (Fietstelweek, FTW) (Cycling Intelligence, 2021) and municipal vehicle counts. Here the FTW data was used for the hourly variations and the municipal counts for calibration. The motor vehicle volumes originate from hourly motorised vehicle count data and municipal traffic models.

Figure 9 shows the bicycle and motor vehicle volumes per municipality, where the bicycle oriented city centres of Amsterdam and Utrecht are clearly visible. In Rotterdam the predicted bicycle volumes are much higher than the other municipalities due to a low participation of the Bicycle Counting Week and count loops mainly located at high volume locations (figure 10). The higher exposure levels on bicycle facilities, and the low number of bicycle streets in Rotterdam, may result in a relative overestimation of the crash rates on bicycle streets.

Figures 10 and 11 show that the bicycle volumes on bicycle streets are often higher than on other facilities in the same municipality. The motor vehicle volumes are comparable with or lower than those on residential roads. This suggests that existing bicycle streets indeed function as main cycling routes and access roads for motor vehicles.

Figures 12 and 13 provide additional descriptives of the traffic volume data in boxplots. The distribution of high-low bicycle volumes is equal over bicycle streets, lanes, and paths. Also, the motor vehicle volumes on bicycle streets all lie within a small, low volume, range.



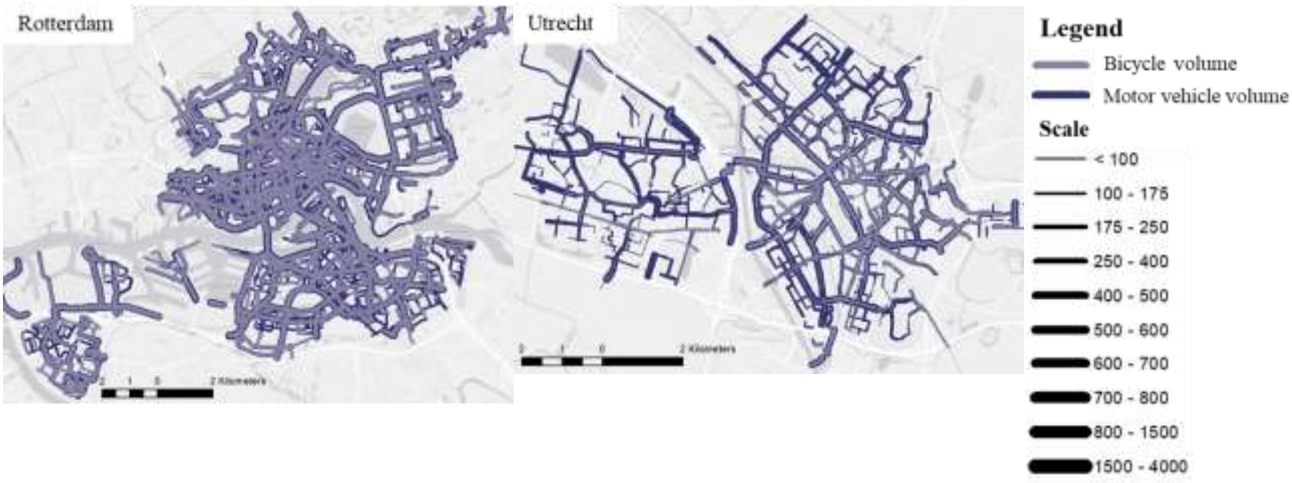


Figure 9 Average hourly bicycle and motor vehicle volumes

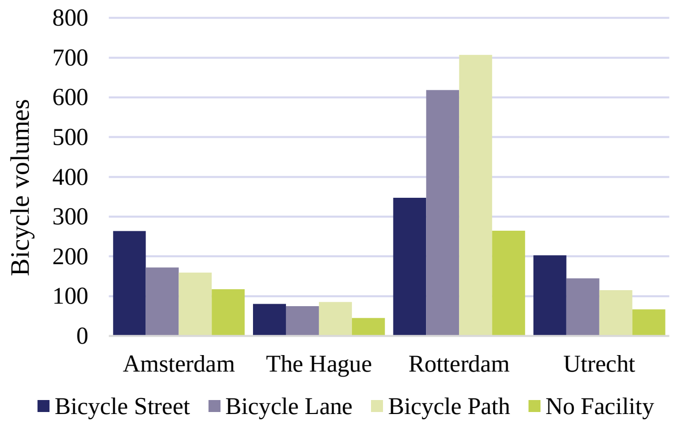


Figure 10 Average bicycle volumes per municipality and facility

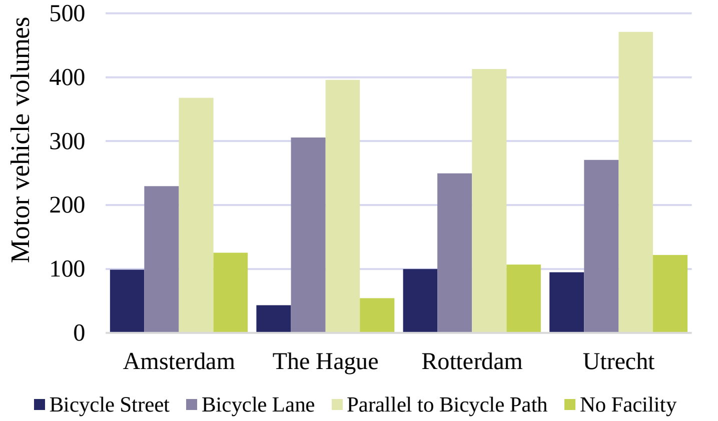
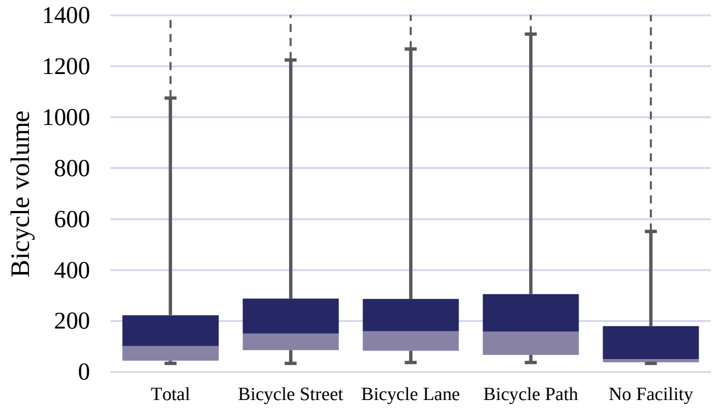
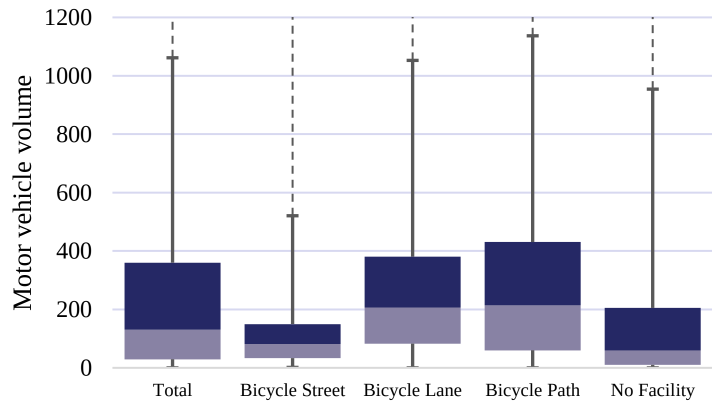


Figure 11 Average motor vehicle volumes per municipality and facility



Max	3143	1595	2334	3143	2236

Figure 12 Box-plot bicycle volumes
*Note: Positive error bar is 3*SD from the mean*



Max	2784	1566	2086	2452	2784

Figure 13 Box-plot motor vehicle volumes

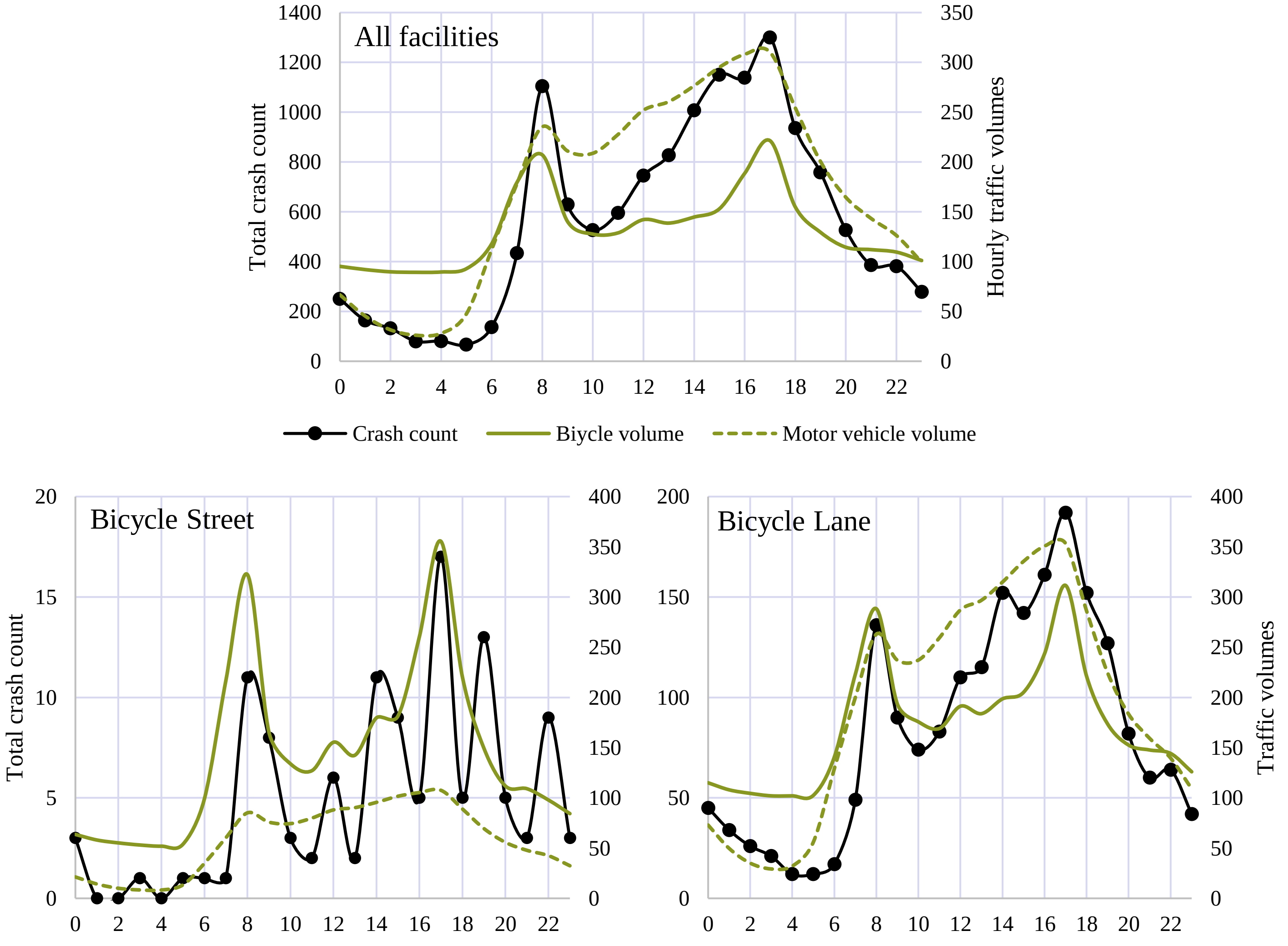
Looking at the temporal variations of the traffic volumes, figure 14 shows that the hourly variations are not comparable between the bicycle facilities. For example, the difference between rush and non-rush hour bicycle volumes on bicycle streets is much larger than on the other facilities, while on average the bicycle volumes of bicycle streets, lanes, and paths are comparable. It is expected that the effect of bicycle and motorised vehicle volumes on bicycle crashes can be captured more accurately when disaggregating between time periods in the analysis. As crashes are rare events, high disaggregation of the data is be prevented by averaging hourly volumes into four time intervals (table 3).

Night-time events are excluded from the study for two reasons: 1) The used traffic volume models overpredict between 0:00-6:00, creating an imbalance in the crash rates between time periods that cover both day and night (e.g. average), and those covering only daytime hours (e.g. rush), and 2) evening and night crashes can hardly be explained by exposure (Uijtdewilligen, et al., 2022), since factors such as cycling (or driving) under the influence of alcohol are the main predictors (Dozza, 2017). Thus, additional crash characteristics should be accounted for when including night-time crashes, which is out of the scope of this study.

Table 3 Time intervals and hours t per week

Interval T	Days	Hours
Day	Mon-Sun	7:00-21:59
Rush	Mon-Fri	7:00-8:59 and 16:00-18:59
Non-Rush	Mon-Fri	9:00-15:59 and 19:00-21:59
Weekend	Sat-Sun	7:00-21:59

Figure 14 shows, in addition to the hourly traffic volumes, also the hourly variations in crash counts. Between 12:00 and 16:00 an increase in crash counts is observed on bicycle lanes, paths and residential roads, while the bicycle volumes remain equal. This suggests bicycle crash frequency is not only strongly related to bicycle exposure but also to the number of motor vehicles. Because of this, and the prior found associations in the literature, motor vehicle volumes are included in the traffic safety models.



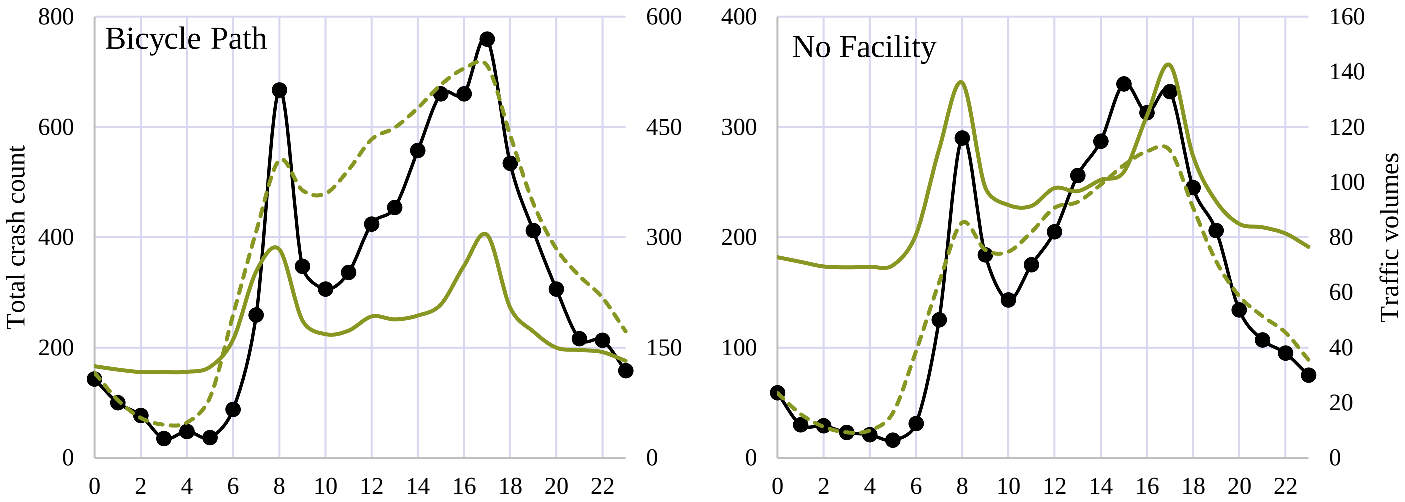


Figure 14 Hourly variations in crash counts and traffic volumes, total and per bicycle facility; a) All facilities b) Bicycle Street, c) Bicycle Lane, d) Bicycle Path, e) No Facility; Primary vertical axis: Total crash count, Secondary vertical axis: Hourly traffic volume in hundreds.

4.4 Environmental variables

Zone specific environmental variables, i.e. population density, median income level, age demographic represented as population factor, and the mixed land use index are included in the analysis. The Mixed use Index (MXI) is the ratio of living area over the total area (Hoek, 2008). The population factor (PF) is developed by Ulak et al. (2017), and is a measure that incorporates the number of households and the counts and percentage of a certain age group per zone i. This factor is a more adequate method to reflect the possible effects of the population on crashes, and is calculated as follows:

$$PF_{ij} = \frac{A_{ij}}{H_i} \times \frac{A_{ij}}{\sum_i A_{ij}} \times 10.000 \quad (1)$$

where A_{ij} is the count of people in age group j and H_i the number of households. The multiplication factor 10.000 prevents substantially small PFs.

5 Methodology

After a description of the study area, this chapter addresses the methodological steps taken in this study. For the first part of this study, these include the calculation of crash cost rates, statistical hypothesis tests on these rates, and the development of Tobit regression models using adaptive synthetically resampled data. Second, the conflict study methodology is described, consisting of the selection of bicycle streets, video data collection, and the observation and analysis approach.

5.1 Study area

The study area consists of the four largest municipalities in the Netherlands, i.e. Amsterdam, Rotterdam, The Hague, and Utrecht (Figure 15), with a total population of 2.45 million (CBS, 2022). The municipalities were selected based on the number of bicycle streets, and the availability of modelled traffic volumes. Figure 16 summarizes the ratios of bicycle facilities per municipality and the total road lengths. Out of the 2,487 km bicycle infrastructure in this study, 28,6 km is bicycle street (~1%).

Figure 15 Selected municipalities in the Netherland. a) Amsterdam, b) The Hague, c) Rotterdam, d) Utrecht

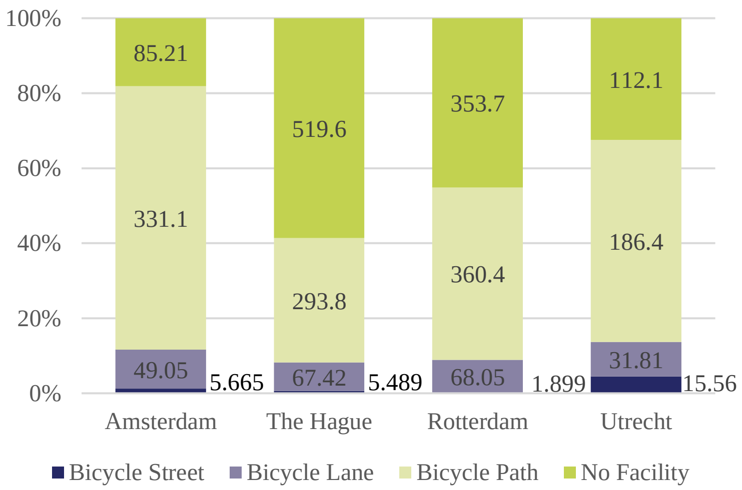


Figure 16 Network length of bicycle infrastructures per municipality with labelled kilometres

5.2 Crash cost rate estimation

This study adopts a segment based safety analysis. The crash cost rate was calculated for four time periods based on the amount of crashes on a link, the exposure at the time interval, the link length, and the social costs of the crash depending on the severity level. The severity weights W_j are based on the social costs SC of a crash type j, estimated by Wijnen (2022) (Equation , table 4). These social costs depend on various expenses, such as intangible, material, medical, and traffic jam costs. The intangible costs are based on the results of the Value of Road Safety (VALOR) study (Schoeters, et al., 2022). Here the willingness-to-pay (WTP) for a reduction of crash rate is expressed as the 'Value of statistical life' (VSL) and 'Value of statistical serious injury' (VSSI).

$$W_j = \frac{SC_{fatal}}{SC_j} \times 10^3 \quad (2)$$

Table 4 Social costs and crash severity weights

Social costs [x1000 €]		W
Fatal	6496	107,143*
Severe injury	696	107.143
Light injury	51	7.851
PDO	3	0.462

** Fatal crashes are weighted equal to severe injury crashes*

The crash cost rate for a link i during interval T per million kilometres is calculated by:

$$CCR_{iT} = \frac{\sum_{n=1}^{j} C_j \times W_j}{y_i \times L_i \times BC_{iT}} \times 10^6 \quad (3)$$

where the crash cost rate CCR depends on the sum of observed crash severities, with C_j the amount of crashes of severity type j and W_j is the weight for severity type j (from Equation 2). L_i is the length in km of link i. The crash rate is expressed annually by dividing with y_i (the years the facility existed within the period 2016-2021), which is assumed 6 for all links except for some bicycle streets. BC_{iT} is the annual number of cyclists in time period T.

Figure 17 shows that the number of zero and non-zero crash links per facility and time period ranges from 65% (average - bicycle lane) to 95% (weekend – no facility). The time periods rush, non-rush, and weekend have higher level of zero crash links as they consist of sections of the week average period. Furthermore, the non-observations differ also between facilities, where they are highest for bicycle lanes. Next, a data distribution overview of the non-zero crash cost rates is provided in figure 18. The distribution of crash cost rates are comparable between all facilities but bicycle streets. The higher crash cost rates on bicycle streets are in line with the higher ratio of severe and fatal crashes (see chapter 4.2 Crash data, figure 5).

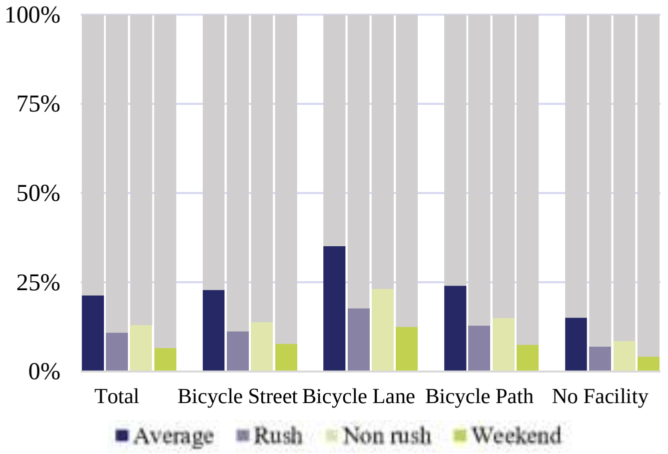


Figure 17 Distribution zero (coloured) and non-zero (grey) crash count links

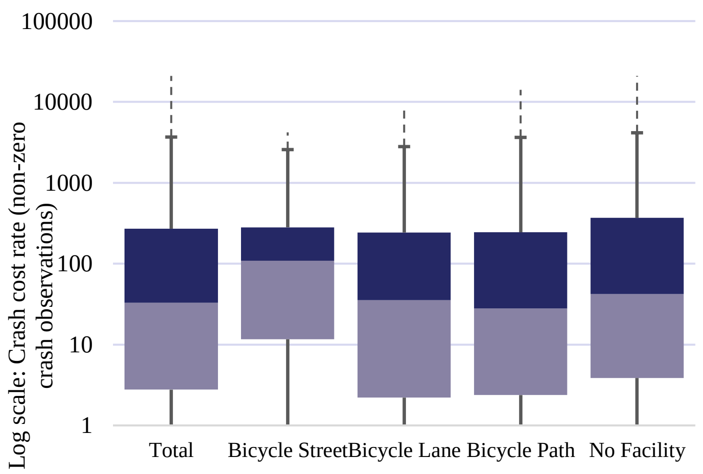


*Figure 18 Box-plot Log crash rate of non-zero crash links. With the upper error line 3*SD; the dotted error line the outlier range*

5.3 Crash cost rate analysis

Two methods are applied for the comparison of the crash cost rates: 1) statistical testing for significant differences in the average rates, and 2) regression modelling to account for external factors. With statistical hypothesis testing it can be decided if a data sample is typical for the population or if they significantly differ (Emmert-Streib & Dehmer, 2019). Two sample z-tests are used to test the differences between average crash cost rates of the bicycle facilities, at different time periods.

The Tobit model, introduced by Tobin (1958), is a type of regression model in which the dependent variable is censored in some way. This model is suitable for crash modelling as it considers the lack of observation, in this case crashes, as censored. Crash rates are assessed over a limited period of time, meaning there is a likelihood that zero crashes are observed during analysis period. Applying conventional models, such as Poisson and negative binomial regression models, to censored data would result in biased and inconsistent parameter estimates, as zero values would be seen as zero risk (Lord & Mannering, 2010; Mannering & Bhat, 2014), rather than as segments at which crashes are not observed but the probability of a crash exists (Anastasopoulos, Tarko, & Mannering, 2008). The significant amount of zero's in the data is dealt with by splitting the road segments into crash-free and crash-prone states (Lord & Mannering, 2010). Using a right-limit of zero, the Tobit model is expressed as follows:

$$Y_i^* = \beta X_i + \varepsilon_i, \quad i = 1,2, \dots, N$$
$$Y_i = \begin{cases} Y_i^*, & Y_i^* > 0 \\ 0, & Y_i^* \leq 0 \end{cases} \tag{4}$$

where Y_i is the dependent variable at roadway segment i, N is the number of observed segments, βX_i is the combination of vectors of the parameter estimate and the independent variable, and ε_i is a normally and independently distributed error term with zero mean and constant variance. Finally, Y_i^* is the implicit stochastic index which is only observed when above zero.

Anastasopoulos et al. (2008) was the first to apply the Tobit model to in a traffic safety context, by analysing accident rates as an continuous variable that is left-censored at zero. Following, recent modelling approaches include a random parameter Tobit model (Anastasopoulos, Mannering, Shankar, & Haddock, 2012), a multivariate random parameter Tobit model (Ulak, Ozguven, Vanli, Dulebenets, & Spainhour, 2018), and a Bayesian random parameter Tobit model (Chen, Sze, Chen, Labi, & Zeng, 2021b).

Two types of regression models were developed: 1) a model for each time period with all bicycle facility links, where the bicycle facilities are modelled as categorical variables with bicycle street as the reference, and 2) separate models for each bicycle facility per time period. Similar to the first model type, an additional model is developed to analyse temporal differences in crash cost rates, with average (0) and weekend (1) as a categorical variable. In all models, the censored dependent variable is crash cost rate, and the independent variables consist of traffic, road design, socio-economic, and demographic characteristics (table 5 and 6, Appendix A).

To avoid multicollinearity in the regression models, the variables were tested for high correlation by calculating the Pearson correlation coefficients (figure 19). Medium levels of correlation were found between the facility types, the population factors, and between motor vehicle volumes and speed limits. However, these results don't show reason to exclude variables from the models.

For comparability of the regression coefficients, they were standardized by ordinary sample standard deviations (Siegel & Wagner, 2022). Standardization is needed as the regression coefficients are expressed in the predictor variable unit, making them incomparable. The standardized regression coefficients β^*, as calculated from Equation 5, are in units of standard deviations of Y per standard deviation of X. The standardized coefficients represent the linear increase of the latent variable (Y_i^*) for each unit increase of the predictors.

$$\beta^* = \beta_i * {SD_{X_i}}/{SD_Y} \tag{5}$$

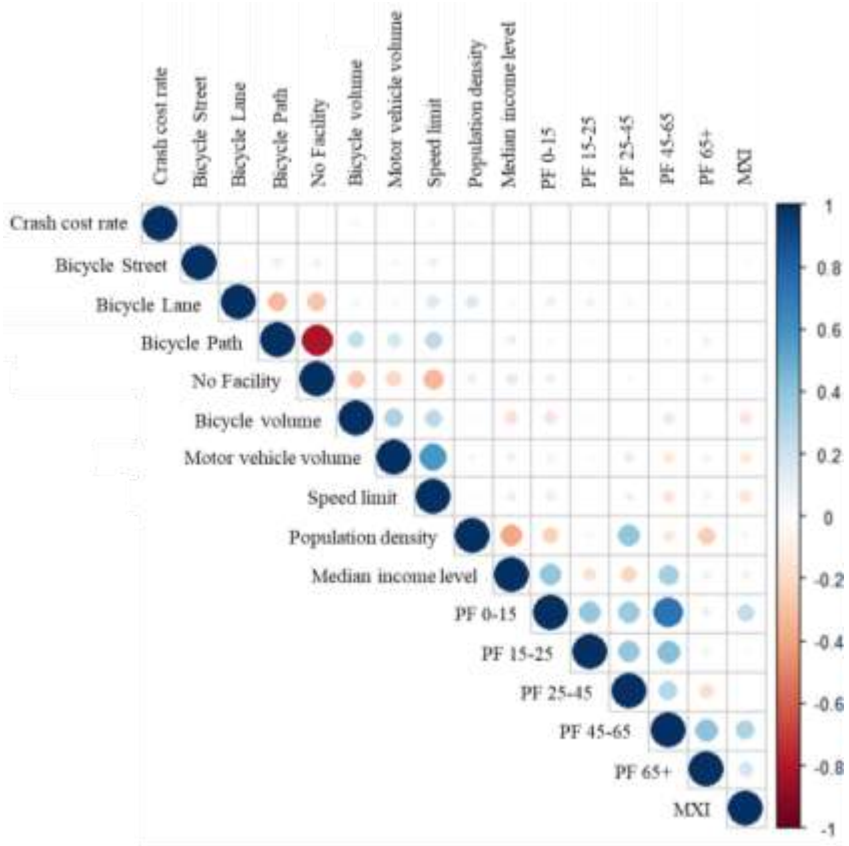


Figure 19 Correlation matrix

5.4 Adaptive synthetic sampling (ADASYN)

As our interest group (bicycle street) contains only 1% of the studied network, the dataset is imbalanced, where the majority overpowers the minority. Such datasets suffer from internal model biases (Morris & Yang, 2021), and it can be difficult to model the effects of the minority classes. This issue can be handled by different resampling methods, either under- or over-sampling. Over-sampling methods are especially useful in crash cost rate modelling where the data set consists of large amounts of zero crash segments. This oversampling method has been successfully applied and validated in traffic safety studies, and was found to provide better model results compared to non-adaptive resampling methods such as SMOTE (Synthetic Minority Oversampling Technique) (You, Wang, Fang, & Guo, 2017; Morris & Yang, 2021).

In this study the *Adaptive Synthetic Sampling Approach for Imbalanced Learning* (ADASYN) method is applied to synthetically generate more “bicycle streets”. The ADASYN method is adaptive in the way that it weights outlier minority points more heavily and more synthetic points are generated near these outliers. This is beneficial as these rare outlier points are often difficult to model. A balance level $\beta = 0.05$ (i.e. the minority class is brought to 5% of the majority class) is used, such that the level of resampled data is minimal while the model performance (significance of coefficients) is optimized.

Table 5 Descriptive Statistics of the explanatory and response variables of the all links regression model

	Mean	Med.	Min	Max	St.D.	Description & source
Crash cost rate						
Average	80.26	0	0	20997	529.5	Crash cost rate per million km, for each time interval
Rush	87.31	0	0	37638	893.7	
Non-rush	87.20	0	0	45004	774.3	
Weekend	62.31	0	0	53641	817.9	
Motor vehicle volume						
Average	233.3	129.4	0	2784	276.2	Motor vehicle volumes [vehicles/hour]
Rush	295.1	164.4	0	3893	350.5	
Non-rush	230.6	125.7	0	2637	272.7	

Weekend	187.6	101.1	0	2104	224.2	
Pop. Density	8307	7655	140.9	19108	3831	Inhabitants per km2 [inh/km2]
Median Inc.	31961	28000	8400	58200	9830	Median income level in area [€]
Pop. factor						
15-25	11.28	5.829	0	60.55	8.686	Population factor per age group
45-65	22.00	13.77	0	82.52	15.90	
65+	14.85	5.66	0	79.68	14.08	
MXI	0.731	0.780	0	0.960	0.370	Mixed land use index [0-1]

Table 6 Descriptive Statistics of the explanatory and response variables of the bicycle street regression model

	Mean	Med.	Min	Max	St.D.	Description & source
Crash cost rate						
Average	77.5	0	0	4207	352	Crash cost rate per million km, for each time interval
Rush	54.2	0	0	3725	281	
Non-rush	49.4	0	0	2379	213	
Weekend	128.93	0	0	10031	831.7	
Motor vehicle volume						
Average	120.9	97.7	1	1566	131.1	Motor vehicle volumes [vehicles/hour]
Rush	124.2	94.9	2	1935	162.5	
Non-rush	98.7	79.7	2	1567	128.40	
Weekend	94.2	74.0	1	1257	105.1	
Pop. Density	8863	7832	1282.9	18591	3770	Inhabitants per km2 [inh/km2]
Median Inc.	31100	27600	8400	54400	9567	Median income level in area [€]
Pop. factor						
15-25	14.72	12.282	0.742	60.55	9.891	Population factor per age group
45-65	24.29	18.59	1.043	82.52	16.29	
65+	13.46	10.43	0.453	57.03	11.77	
MXI	0.662	0.730	0.03	0.930	0.188	Mixed land use index [0-1]

5.5 Conflict study

A traffic conflict is “an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged” (Amundsen & Hydén, 1977). This study includes a conflict study on four bicycle streets, for which bicycle streets are selected, video data is collected and observed, and outcomes are analysed.

5.5.1 Bicycle street selection

A conflict study was performed on four bicycle streets (for detailed design information see Appendix B). The streets were selected such that they vary on the main factors affecting near crash event occurrences on bicycle streets following the literature (see figure 2): motor vehicle and bicycle volumes, road width, and rabat strip width/median presence. Figures 20 and 21 provide an overview of these variables for the selected streets. The bicycle volumes range from 100-400 cyclists/h on narrow streets to 300-1000 cyclists/h on wider streets. The modelled motor vehicle volumes are consistent throughout the day, but vary strongly between all streets. For practical reasons all bicycle streets are located in the same municipality: Utrecht (figure 22).

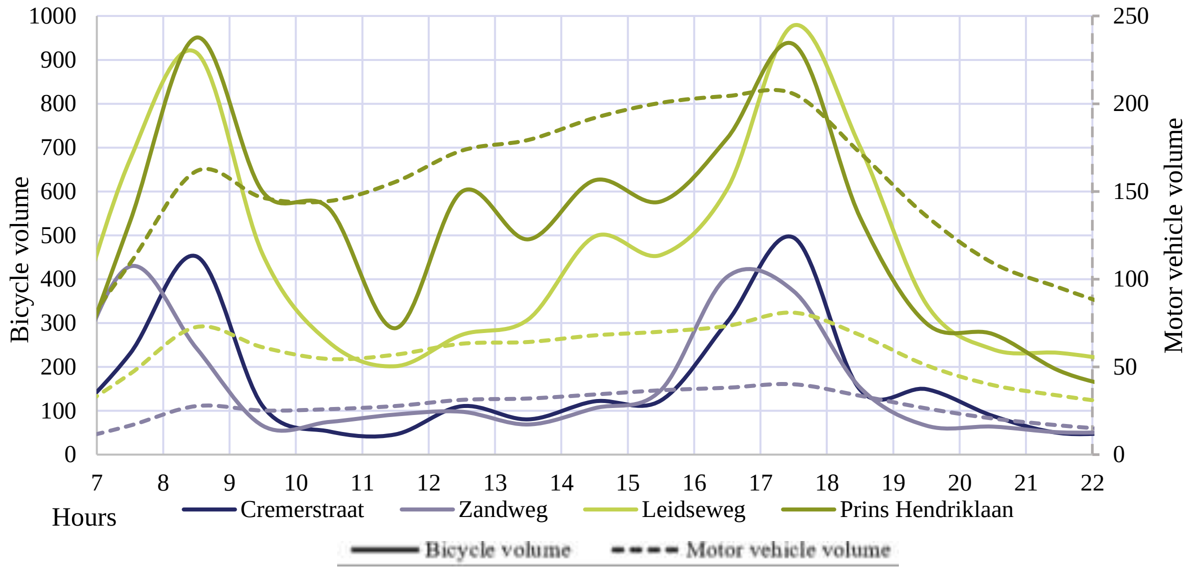


Figure 20 Modelled bicycle and motor vehicle volumes on the conflict study bicycle streets
Note: no modelled motor vehicle volumes for the Cremerstraat.

Figure 21 Road profiles of the four conflict study bicycle streets

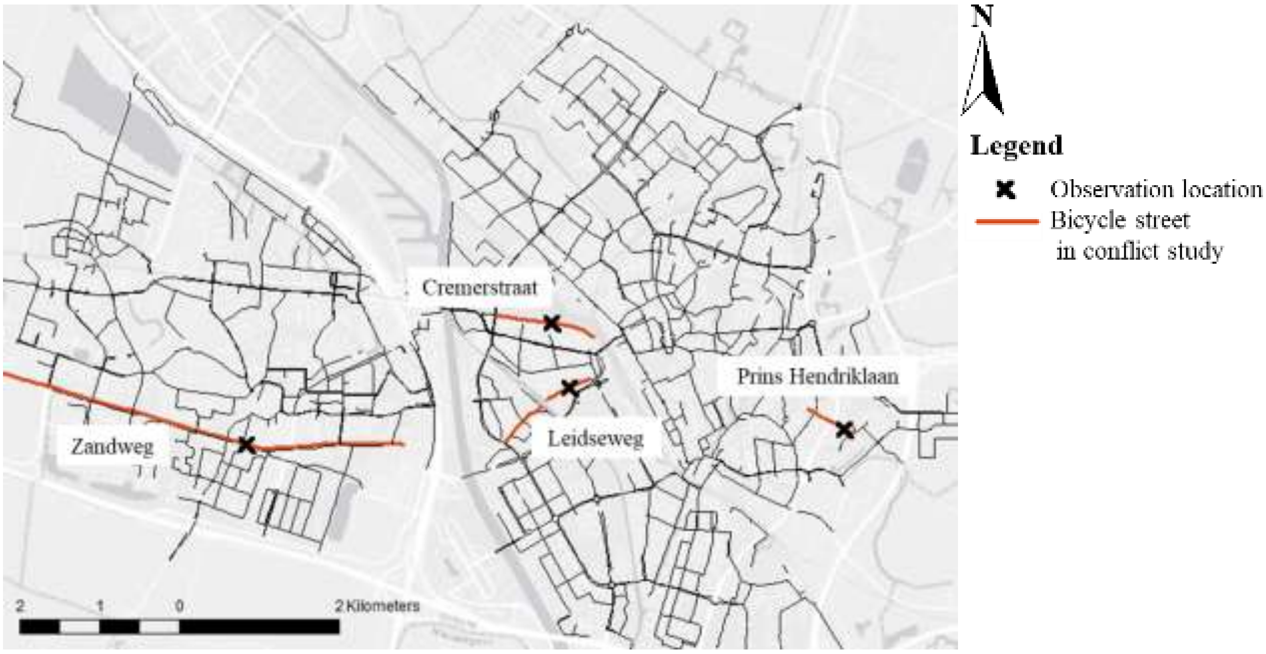


Figure 22 Locations conflict study bicycle streets and video observation points

5.5.2 Video data collection and observation

On each bicycle street video data was collected between 7:00-11:00 and 14:00-19:00, covering both rush and non-rush hours, on a weekday in March or April. Due to the limited resources of this study, the video data was collected from a dashboard camera in a parked motor vehicle.

The conflicts are defined based on the conflict severity scoring system, which distinguishes between three types of interactions between road users, developed and successfully used by Godefrooij & Hulshof (2017) (table 7). This system is a variation to the Dutch conflict technique (DOCTOR), which uses two parameters to manually determine the conflict severity: 1) the probability of a collision, as the TTC or PET; and 2) the injury level, as an estimation of vulnerability based on speed, mass and seriousness of avoidance action (Kraay & van der Horst, 1988; Kraay, van der Horst, & Oppe, 2013). Delbressine (2013), Godefrooij & Hulshof (2017), and Van Boggelen & Hulshof (2019) are examples studies that applied (variations of) the Dutch conflict technique (DOCTOR) to analyse bicycle street safety.

Table 7 Conflict severity scoring on bicycle streets from Godefrooij & Hulshof (2017)

Score	Overtaking & oncoming traffic	Car-behind-bicycle
1	No hinder of each other, safe situation.	At a comfortable distance.
2	Adjusted behaviour ("make space"), but safe situation.	Close to the cyclist (bothersome).
3	Bothersome (high speed, at small distance), not comfortable, but through adjusted behaviour the probability of a collision is small.	Hard breaking, close to cyclist (dangerous).
4	Very bothersome, breaking or evasive manoeuvre is necessary to prevent collision.	
5	Very dangerous (physical contact), in some cases leading to a crash.	

Note: The red line notates the threshold between a safe interaction between road users (above) and a conflict (below)

A total of 36 hours of video was analysed and the characteristics in table 8 were collected per interaction. Since the video data is manually analysed, resources are limited, and the aim is to analyse unsafe events, only interactions that involve a motor vehicle or might become critical due to the road profile are noted. Interactions are "might become" critical when the required road width to facilitate all users and their safe passing distances is more than, equal to, or close to the actual road width (CROW fietsberaad, 2016).

Table 8 Characteristics per interaction

ID	Conflict ID.
Time	Hour of conflict in real time.
Type conflict	Oncoming traffic; Overtaking with oncoming traffic; Overtaking without oncoming traffic; Motor vehicle behind cyclist.
Severity scale	Table 7.
Evasive action	None; Breaking; Change trajectory; Both.
Interaction	Interaction profile. E.g. Cyclist-MV;Cyclist (- = overtaking, ; = oncoming)
Participants	Road users; either passive (overtook), active (overtaking) or oncoming.
Position participants	Position on the road. E.g. on rabat, right hand side, left hand side.
Estimated speed	Estimated speed based on travel time over set distance.

5.6 Analysis of conflict observations

The noted interactions are analysed to provide a insight into general patterns of unsafe events on bicycle streets. For this, the conflict frequencies per type of conflict and studied street, and the conflict rate per road user type is calculated (number of conflicts one road user is involved in per kilometre). These conflict frequencies and rates per time period (average, rush, non-rush) are then tested for correlation with the traffic volume counts, as these are the main known predictors of bicycle street performance/occurrence of unsafe events.

6 Results and discussion

6.1 Comparison of the crash cost rates

To conclude on how bicycle street safety compares with other facilities, the crash cost rates are compared through: 1) statistical hypothesis tests on the average rates, and 2) regression models to account for external factors.

6.1.1 Average crash cost rates

The statistical tests show that bicycle paths are significantly safer for cyclists than other facilities on average, and during rush and non-rush hours. This is in line with the general perception that separating bicycle and motor vehicle traffic benefits cyclists' safety (van Petegem, Schepers, & Wijlhuizen, 2021; Winters, Babul, Becker, & et al., 2012; Schepers P. , Heinen, Methorst, & Wegman, 2013). The literature is indecisive on the benefits or downsides of bicycle lanes, compared to regular residential streets. For example, van Petegem et al. (2021) did not find differences between the two, while Chen, et al. (2021a) showed lower risks on bicycle lanes. Contradictingly, this study shows higher crash rates on bicycle lanes, compared to residential roads.

When comparing the crash rates per time period on a facility, the weekend rates are significantly lower than any other time period on all facilities but bicycle streets. This high crash rate on bicycle streets during the weekend may be the result of the small data sample and unusually many (severe) crashes. High risks during the weekend are unlikely as this study includes only crashes from 7:00 to 22:00, thus excluding dangerous periods (weekend 0:00-6:00) due to darkness and driving under influence of substances (Dozza, 2017). Lastly, crash cost ratios are (slightly) higher outside of rush hours than within.

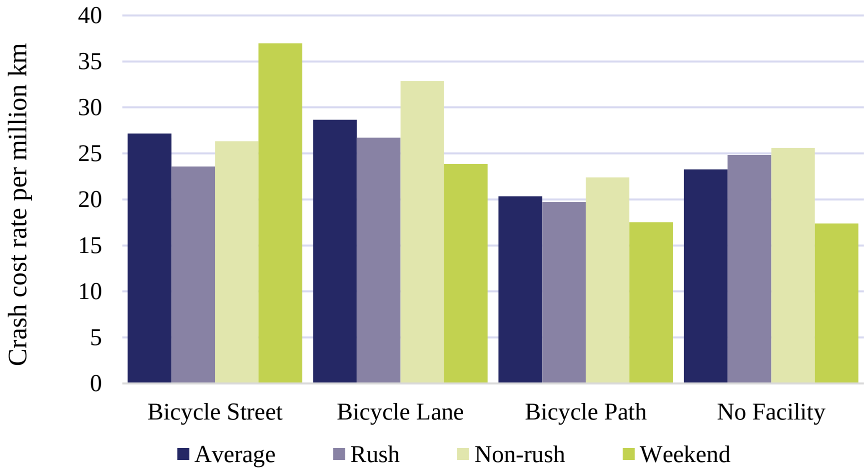


Figure 23 Average crash cost rate, per bicycle facility and time interval

Both figures 8 and 10 showed differences between the municipalities in terms of crash densities and bicycle volumes. The resulting crash cost rates per municipality (figure 24) are therefore not surprising. Firstly, in Rotterdam the crash cost rates are very low due to the high modelled bicycle volumes. Furthermore, the lower rates in Utrecht are likely linked to the low crash densities. The imbalances in the traffic volume and crash data between the municipalities may affect the safety comparison of the facilities as the distribution of the facility types is not equal over the municipalities. Most importantly, the low number of bicycle streets in Rotterdam in combination with the high bicycle volumes result in an underestimation of non-bicycle street facilities. In addition, the high number of bicycle streets in Utrecht in combination with the low crash density, likely results in an underestimation of crash rates on bicycle streets. The sensitivity of the results to the municipal variations is unclear as single-municipality models do not provide significant results.

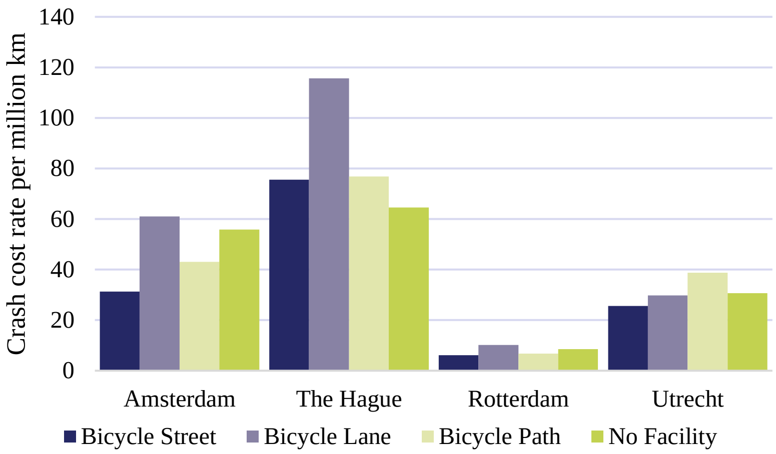


Figure 24 Crash cost rates per municipality and facility

6.1.2 All facilities regression model

Four Tobit regression models (i.e. for each time period) describing the crash cost rate in terms of the facility type, motor vehicle volumes and environmental variables are developed (figure 25).

The bicycle facility type is modelled as a categorical variable, meaning that each dummy variable is compared with the reference group: bicycle street. A negative regression coefficient means that the crash cost rate is lower for the dummy variable than for the reference group. Furthermore, a statistically significant regression coefficient means that the crash rate relationship with the reference group is also statistically significant.

Thus, these models show that for each time period the crash cost rate on bicycle streets is significantly higher than on any other bicycle facility, when controlling for traffic and environmental variables. It should be noted that without resampling, the crash cost rate differences between bicycle streets, and bicycle lanes and paths are not significant. The fact that residential roads have the highest safety difference with bicycle streets contradicts with the average crash cost rates of figure 23, where bicycle paths were found to have to lowest risk. This can be explained by the fact that the models control for motor vehicle volumes and speed limit, which are positively associated with crash cost rates, and generally higher on (roads parallel to) bicycle paths.

Similar to the literature findings, increased motor vehicle volumes are associated with reduced safety, in terms of crash rates (Uijtdewilligen, et al., 2022), and BMV crash frequencies (Chen & Shen, Built environmnet effects on cyclist injury severity in automobile-involved bicycle crashes, 2016; Asadi, Ulak, Geurs, Weijermars, & Schepers, 2022). However, the effect of motor vehicle volumes on the crash cost rate is small. This can be due to the (slight) correlation with the bicycle facility type, and the speed limit (figure 19).

Next, population density has a significant positive relation with crash cost rate in all models. Thus, higher population densities are not only associated with reduced safety in terms of higher crash frequencies (Lee & Li, 2014), but also with crash rates. Other environmental variables such as median income level, and mixed land use index poorly fit the model, meaning they did not benefit the prediction of crash cost rate, and were excluded.

The coefficients of the population factors (PF) are minimal but negative. Indicating that a reduction of the age groups 45-65 and 65+ is associated with increased crash rate. Generally, the effect of elderly is opposite as elderly suffer from more severe injuries (Vanparijs, Panis, Meeusen, & de Geus, 2015; Chen & Shen, Built environmnet effects on cyclist injury severity in automobile-involved bicycle crashes, 2016; Chimba & Musinguzi, 2016). The other age groups were not included in the model as the coefficients were small and not significant.

Finally, lower speed limits are known to benefit safety of cyclists (Schramm & Rakotonirainy, 2009; Lee, Abdel-Aty, & Jiang, 2015). The models show indeed that a reduction in speed limit from 50 to 30km/h reduces crash rate. But considering bicycle streets all have a speed limit of 30km/h in the Netherlands there are no practical implications of this finding for bicycle street safety.

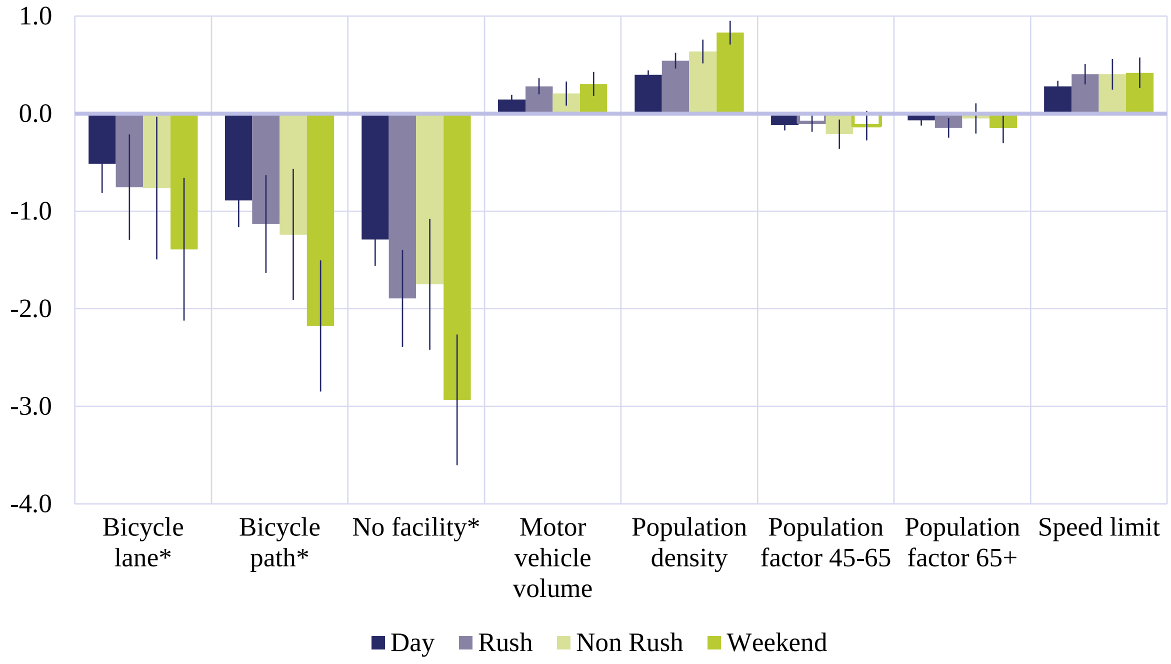


Figure 25 Tobit regression model outcomes: all link model with bicycle facilities as categorical variables
Notes: Filled bars = significant coefficients (p < 0.01); Regression coefficients standardized using SD; Error bars are CI at 95%

In this study, four time period models were created to asses temporal differences in relations between predicting factors and safety, and some small variations in the regression coefficients between the time periods are found. The larger coefficients of the weekend model indicate that during this period the safety differences between bicycle streets and the modelled facilities is also larger, which is in line with findings of the previous section. Figure 26 shows that overall the weekend crash cost rates are significantly lower than the week averages, while previous studies found higher risks during weekends (Chimba & Musinguzi, 2016; Dozza, 2017). However, driving/cycling under the influence of alcohol at night plays a large role in this increased risk, and night-time crashes are not included in this study.

Table 9 Table overview of Tobit regression model outcomes: all link model with bicycle facilities as categorical variables

	Average		Rush		Non Rush		Weekend	
(Intercept)	**-1689**	***	**-5592**	***	**-4261**	***	**-7303**	***
	87.6		*274.0*		*197.7*		*378.5*	
	[-1861,-1517]		[-6129,-5055]		[-4648,-3874]		[-8045,-6561]	
Motor vehicle volume	**0.135**	***	**0.259**	***	**0.188**	***	**0.296**	***
	0.023		*0.039*		*0.034*		*0.061*	
	[0.09,0.18]		[0.183,0.335]		[0.121,0.255]		[0.176,0.416]	
Bicycle Path	**-0.483**	***	**-0.694**	*	**-0.698**	**	**-1.350**	***
	0.142		*0.254*		*0.213*		*0.362*	
	[-0.761,-0.205]		[-1.192,-0.196]		[-1.115,-0.281]		[-2.06,-0.64]	
Bicycle Lane	**-0.833**	***	**-1.041**	***	**-1.133**	***	**-2.113**	***
	0.131		*0.235*		*0.197*		*0.333*	
	[-1.09,-0.576]		[-1.502,-0.58]		[-1.519,-0.747]		[-2.766,-1.46]	
No Facility	**-1.207**	***	**-1.744**	***	**-1.599**	***	**-2.850**	***
	0.130		*0.234*		*0.196*		*0.332*	
	[-1.462,-0.952]		[-2.203,-1.285]		[-1.983,-1.215]		[0.096,-2.199]	
Population Density	**0.374**	***	**0.500**	***	**0.582**	***	**0.806**	***
	0.022		*0.038*		*0.033*		*0.061*	
	[0.331,0.417]		[0.426,0.574]		[0.517,0.647]		[0.686,0.926]	
PF 45-65	**-0.112**	**	**-0.083**		**-0.193**	***	**-0.120**	
	0.026		*0.046*		*0.041*		*0.075*	
	[-0.163,-0.061]		[-0.173,0.007]		[-0.273,-0.113]		[-0.267,0.027]	
PF 65+	**-0.065**	*	**-0.134**	**	**-0.044**		**-0.144**	*
	0.026		*0.047*		*0.040*		*0.077*	
	[-0.116,-0.014]		[-0.226,-0.042]		[-0.122,0.034]		[-0.295,0.007]	
Speed Limit	**0.262**	***	**0.372**	***	**0.369**	***	**0.407**	***
	0.027		*0.049*		*0.042*		*0.078*	
	[0.209,0.315]		[0.276,0.468]		[0.287,0.451]		[0.254,0.56]	

*Note: With the standardized coefficient in bold; the p-value as ***p < 0.001; **p < 0.01; *p>0,05; -p < 0.1; the standard error in italic; the confidence interval at 95% in brackets.*

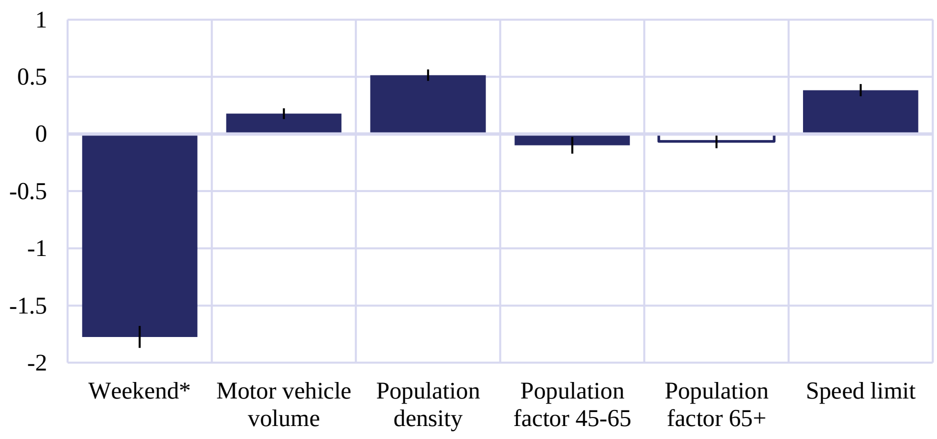


Figure 26 Tobit regression model outcomes: All links with average-weekend as categorical variable

Notes: Filled bars = significant coefficients (p < 0.01); Regression coefficients standardized using SD; Error bars are CI at 95%

Table 10 Table overview of Tobit regression model outcomes: All links with average-weekend as categorical variable

(Intercept)		Motor vehicle volume		Weekend		Population Density		PF 45-65		PF 65+		Speed Limit	
-3848	***	-1.775	***	0.178	***	0.515	***	-0.099	**	-0.065	*	0.384	***
137.3		0.049		0.024		0.026		0.037		0.030		0.027	
[-4117,-3579]		[-1.871,-1.679]		[0.131,0.225]		[0.465,0.565]		[-0.172,-0.026]		[-0.124,-0.006]		[0.331,0.437]	

6.1.3 Regression models per facility

16 Tobit models (four facilities x four time periods) provide further insight in how each independent variable affects cyclists' safety on the respective facility. Figure 27 shows the standardized model coefficients of the bicycle street models, and figure 28 shows the 4x4 models plotted per time period (table overviews in Appendix D).

Bicycle volumes are significant positive predictors of crash rates in separate facility models, at one or more time periods. For bicycle streets specifically, these results suggest that bicycle volumes have a (small) significant impact on crash rates throughout the week. While the literature is clear on the positive relationship between crash frequencies and bicycle volumes (Schipdonk & Reurings, 2012; Asadi, Ulak, Geurs, Weijermars, & Schepers, 2022), the relationships with crash rates is often found to be weak or uncertain (Schepers & Heinen, 2013; Vandenbulcke, et al., 2009).

The motor vehicle volume coefficients are, contrary to expectations based on literature and previous findings of this study (Chen & Shen, 2016; Uijtdewilligen, et al., 2022; Asadi, Ulak, Geurs, Weijermars, & Schepers, 2022) small and not significant. However, during average days and rush hours, bicycle streets with higher motor vehicle volumes are associated with lower crash rates. Van Boggelen & Hulshof (2019) argued that bicycle streets with higher motor vehicle volumes are not negative for cyclists' safety if the road profile is adapted accordingly. However, considering 49% of motor vehicle volumes on bicycle streets are estimated based on the road width, these results are not reliable and motor vehicle volumes on bicycle streets are likely, similar to the average bicycle facility (figure 25), positively associated with safety.

Similar to the full model, on all bicycle facilities an increased population density is associated with increased crash rates. The median income levels and MXI coefficients are only (sometimes) significant in the bicycle street and no facility models. Bicycle streets in high income areas are associated with higher crash rates, while for residential roads the effect is opposite. Thus, turning regular residential streets into bicycle streets in low income areas would benefit bicycle safety, and can be a measure to reduce inequities between socio-economic performance and traffic safety (Asadi, Ulak, Geurs, Weijermars, & Schepers, 2022; Odijk, Asadi, Ulak, & Geurs, 2022).

The association between the population factors and crash cost rate is minor and often not significant in the models. Noteworthy is that bicycle streets in areas with more young people (15-25 year old) are associated lower crash rates during rush hours and higher rates outside rush hours on bicycle streets. This effect may be explained as this groups travel patterns are not fixed to rush hours, and they are generally associated with higher risk levels due to their hazardous travel behaviour, social environment, and risk assessment abilities (SWOV, 2022).

Furthermore, on bicycle streets (during rush hours) higher levels of elderly are linked to increased crash cost rates, while on other facilities the relationship is negative or does not exist. Additionally, on bicycle street in 52% of crashes and elderly was involved (47, 44, 48% for other facilities), and these crashes are of higher severity levels (45% of elderly crashes severe/fatal). These results suggest that bicycle streets add to the inequalities in traffic safety among demographic groups. The complex function and diverse designs of bicycle streets may lack the required perceptible, self-explanatory, relevant, and executable information for elderly (SWOV, 2018).

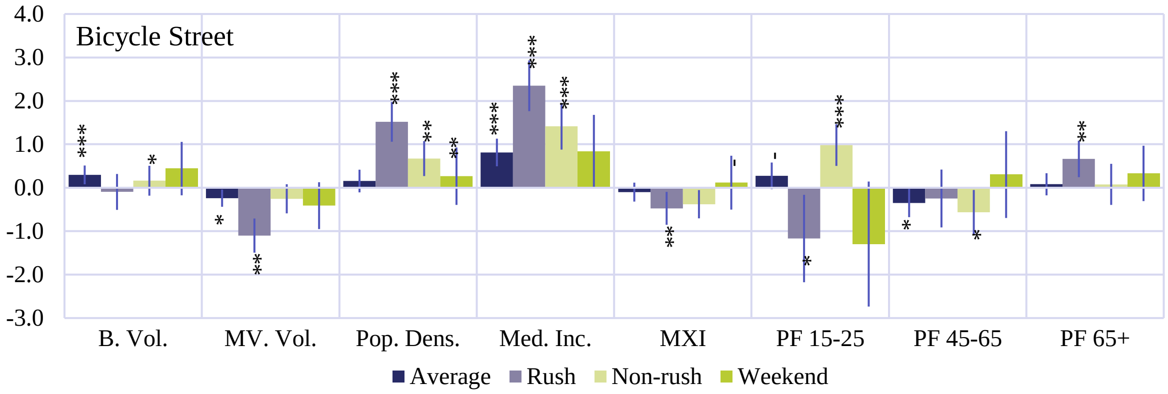
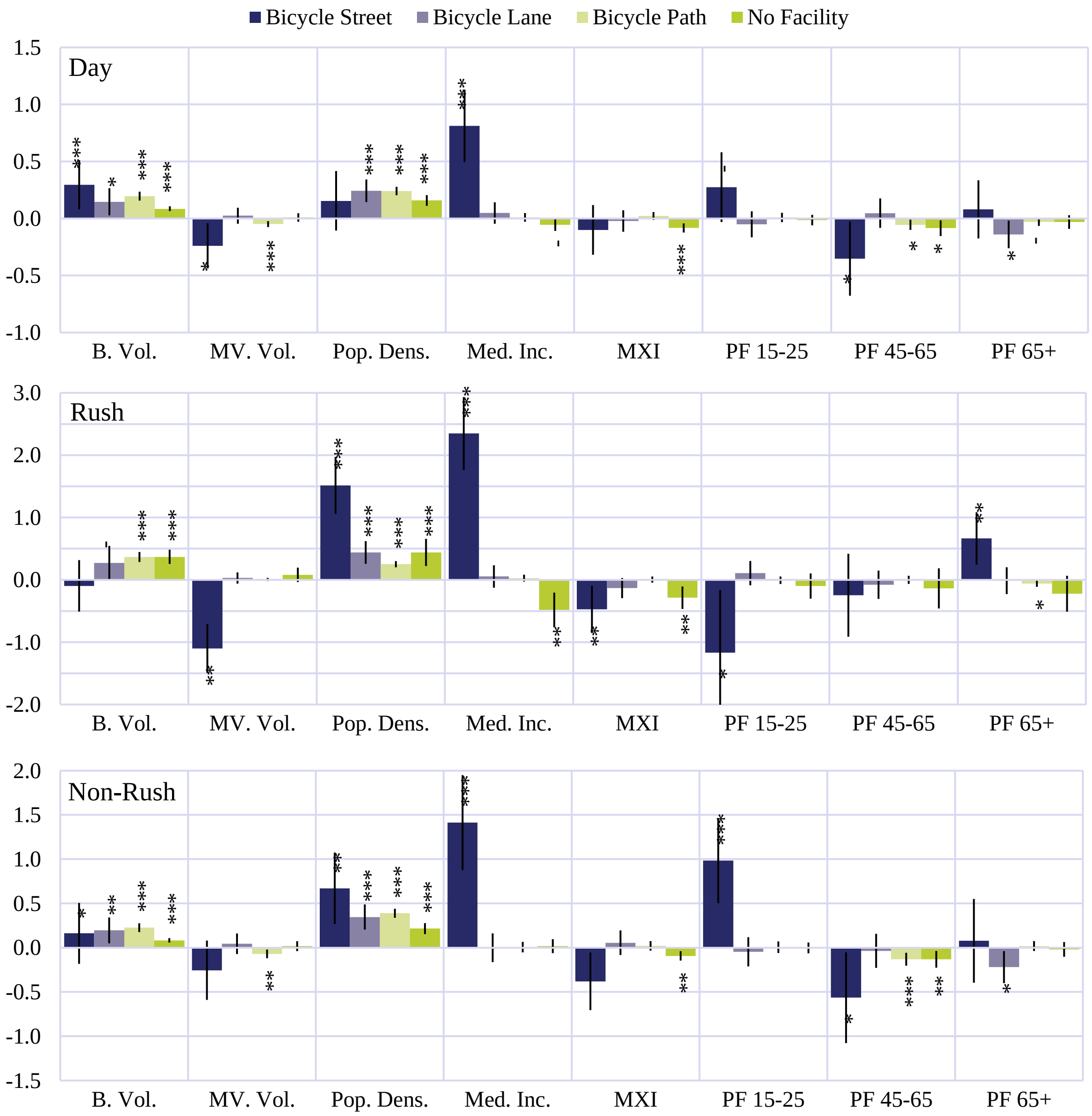


Figure 27 Tobit regression model outcomes: Bicycle street links



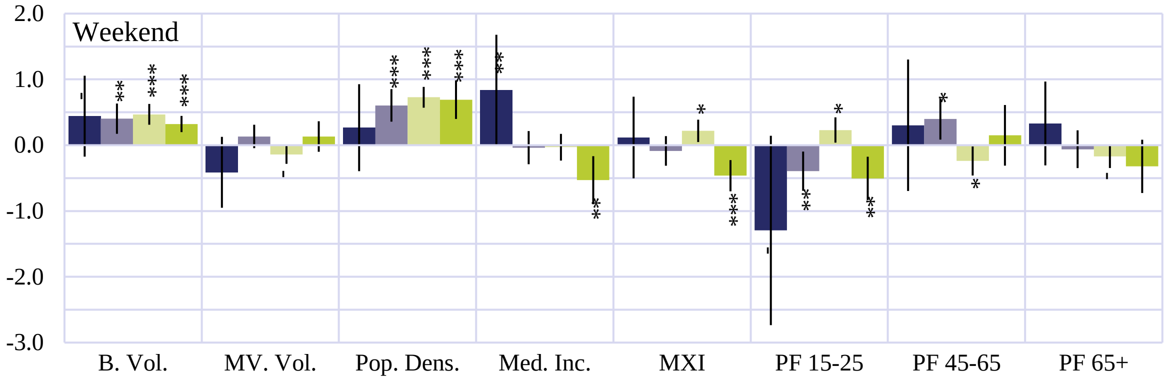


Figure 28 Tobit regression models: Per facility models grouped per time period

*Notes: Significance level p-value as ***p < 0.001; **p < 0.01; *p>0,05; -p < 0.1; Regression coefficients standardized using SD; Error bars are CI at 95%*

6.2 Conflicts on bicycle streets

The observation of 36 hours of video resulted into 1031 safe interactions and 71 conflicts (6.4%). No conflicts of the highest severity level (very dangerous, light physical contact and in some cases leading to a crash) were seen (table 11).

Table 11 Observed interaction severities per interaction type

		No hinder of each other, safe situation.	Adjusted behaviour ("make space"), but safe situation.	Bothersome (high speed, at small distance), not comfortable, but through adjusted behaviour the probability of a collision is small.	Very bothersome, breaking or evasive manoeuvre is necessary to prevent collision.	Very dangerous (light physical contact), in some cases leading to a crash.
	Total*	1	2	3	4	5
Overtaking	696	581	85	28	2	0
Oncoming	257	189	57	11	0	0

		At a comfortable distance.	Close to the cyclist (bothersome).	Hard breaking, close to cyclist (dangerous).
	Total*	1	2	3
MV-behind-cyclist	144	115	27	2

**Due to the manual analysis of the video data only possible critical interactions between road users and interactions with motor vehicles are noted.*

Figure 29 summarizes the conflict frequencies of different types of interactions per bicycle street. The majority of conflicts occurred in *overtaking with oncoming traffic* events (45%), closely followed by situations where motor vehicles abstained from overtaking (*motor vehicle-behind-cyclist* (36%)). The highest conflict frequencies are observed on the Cremerstraat and Leidseweg. Overall, the observed conflicts and their characteristics (i.e. severity, interaction type, involved road users, positions, evasive actions) vary strongly between the studied bicycle streets, likely due to the variations in road profiles and traffic volumes. Some reoccurring characteristics of conflicts are addressed, but this analysis focusses mainly on commonalities between the streets in terms of road user conflict rates and their correlations with traffic volumes. Chapter 9.3 (annex) describes the street specific event in more detail.

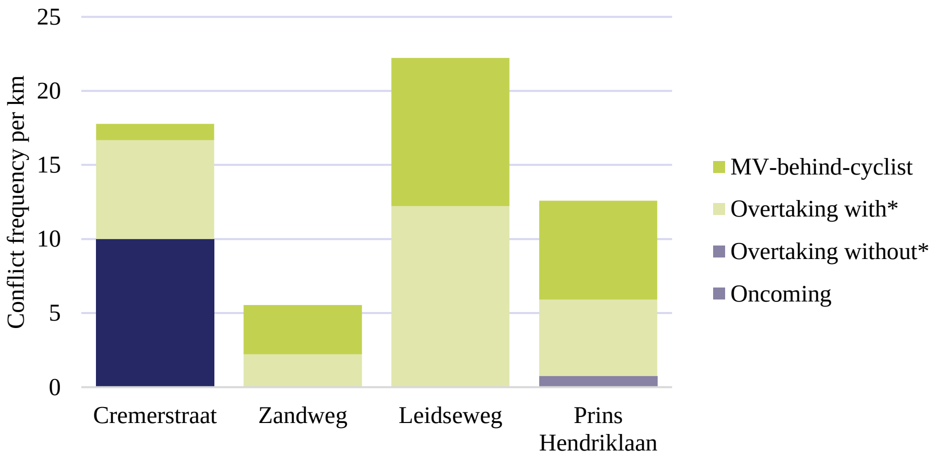


*Figure 29 Conflict frequencies and types of conflicts. *oncoming traffic*

6.2.1 *Conflict involvements of road user types*

From figure 30 it follows that motor vehicles and duo-cyclists are 1.5 to 15 times more likely to get involved in a conflict than regular cyclists. Denvall & Johansson (2013) concluded that duo-cyclists actually benefit from bicycle streets as they provide more space, however these cyclists were involved in 32.9% of conflicts, while they make up 8-20% of cyclists. This conflict study does not allow for the comparison of duo-cyclists' safety between facilities, but the results do show that cyclists cycling in a pair are strongly disadvantaged on narrow and high volume bicycle streets, in comparison with regular cyclists. Poor estimation of the level of duo-cyclists can lead to significant underestimation of expected bothersome and dangerous interactions. Careful evaluation of the ratio of duo-cyclists to be expected is necessary for implementation of a well performing bicycle street.

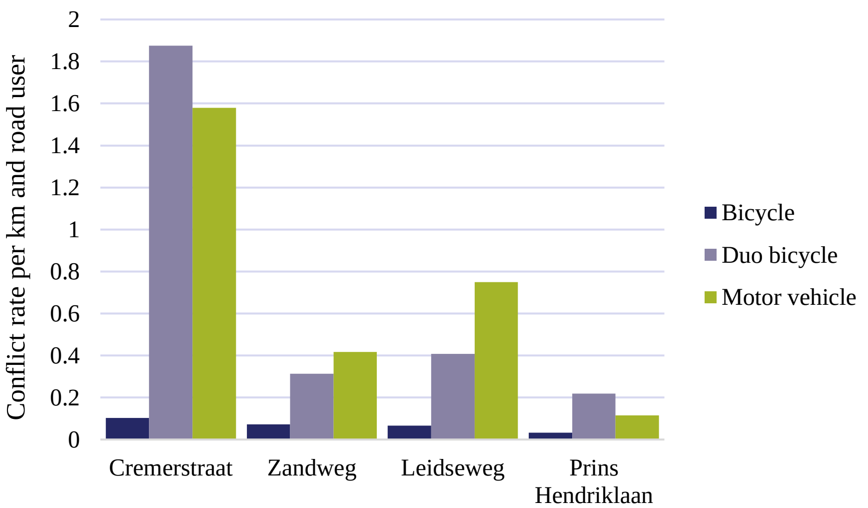


Figure 30 Conflict rate for cyclists and motor vehicles

In addition to the high conflict rate, motor vehicles are involved in 94% of observed conflicts. On a bicycle street motor vehicles have the option to overtake or remain behind the cyclist. While former bicycle street designs aimed to prevent overtaking (Andriesse & Ligtermoet, 2005), and the median still serves as a barrier for motor vehicles to enter the opposite lane (van Boggelen & Hulshof, 2019), overtaking events are not uncommon (66% overtaking, versus 34% motor vehicle-behind-cyclist). Figure 31 summarizes in flow-form the observed safe and dangerous events where motor vehicles approach a cyclist and have the option to overtake or not.

Most motor vehicle involved conflicts (82%) occurred while the road space was sufficiently safe. Main characteristics of unsafe events between motor vehicles and cyclists are: driving speeds above the limit (30 km/h) (24%), cyclists not driving on the right hand side of the road lane (10%), and high volumes of cyclists that reduce the subjectively available space which makes motor vehicles abstain from overtaking (last minute) (17%). It should be noted that speeding only occurred on the widest street, suggesting that roads wider than the minimum required space for safe passing are not desirable.

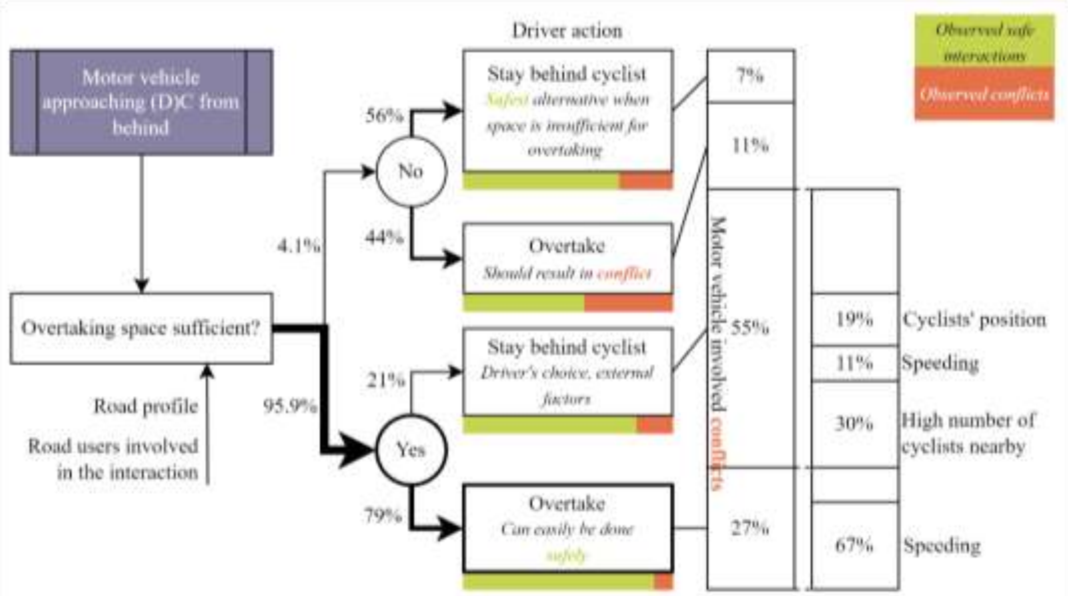


Figure 31 Overtaking versus remaining behind a cyclist; safe and unsafe actions of motor vehicles
**Required overtaking space is based on the profile of cyclist space (CROW fietsberaad, 2016) and a naturalistic study on bicycle lane design on road user widths and passing distances (CROW fietsberaad, 2015)*

6.2.2 Conflict frequencies and rate related to traffic volumes

The crash data analysis showed a positive relationship between bicycle street safety and bicycle volumes, and unreliable results for the relationship with motor vehicle volumes. This subsection addresses the correlation between traffic volumes and occurrences and rates of near-crash events. Figures 32 and 33 show the modelled and counted traffic volumes on the studied bicycle streets. The modelled and counted bicycle volumes are more or less comparable. However, the motor vehicle volumes very strongly, where volumes on the Leidseweg are strongly underestimated and daily variations in volumes on the Prins Hendriklaan are larger than predicted.

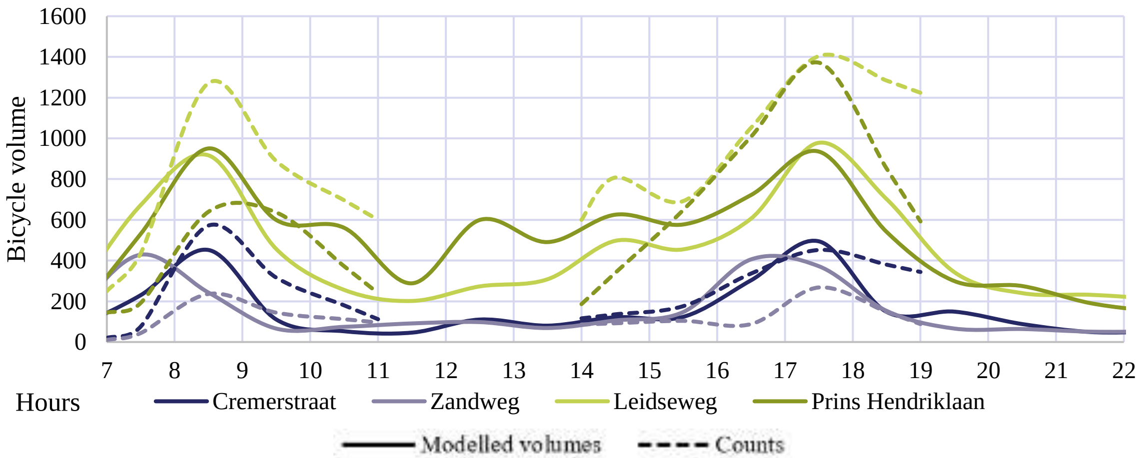


Figure 32 Bicycle volume model estimates and counts on selected bicycle streets

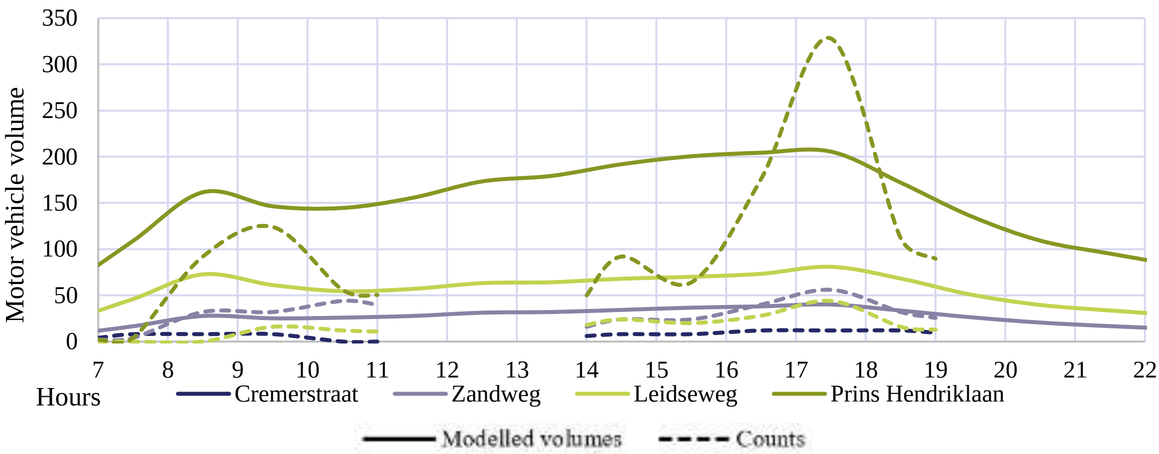


Figure 33 Motor vehicle volume model estimates and counts on selected bicycle streets

The traffic counts are used for the correlation testes between conflict frequencies and rates, and traffic volumes. Positive relationships were found between the number of cyclists involved in a conflict and both the bicycle volumes, and the bicycle-motor vehicle ratio. This is contrary to previous findings of conflict studies on bicycle streets, where no relationship between bicycle volumes and conflict rates was found (CROW Fietsberaad, 2021). On the other hand, crash frequencies are known to increase with bicycle volumes (Asadi, Ulak, Geurs, Weijermars, & Schepers, 2022), making it reasonable that conflict frequencies do as well.

Next, conflict rates for cyclists are positively associated with bicycle intensities outside rush hours, but negatively (though weakly) within rush hours (figure 34). Perception studies found that subjective safety of cyclists is not linked to bicycle volumes (Khut, 2012; Denvall & Johansson, 2013; Olsson & Elldér, 2023). Yet, Godefrooij & Hulshof (2017) concluded that increased bicycle volumes benefit cyclists' safety on bicycle streets. Based on the conflict study findings and the crash cost rate models, this benefit is not apparent.

Average and rush hour motor vehicle volumes are negatively associated with cyclist conflict rates. However, this does not mean increased motor vehicles on bicycle streets benefit safety. Referring back to figure 30, high motor vehicle conflict rates are found on bicycle streets with very low motor vehicle volumes (Cremerstraat and Leidseweg). Therefore it is suspected that, bicycle streets with high bicycle-motor vehicle volume ratios designed to facilitate the high bicycle flow (Godefrooij & Hulshof, 2017), do not properly facilitate interactions with motor vehicles. Based on these findings, leading road user interactions for road design should be those involving motor vehicles, even when volumes are low.

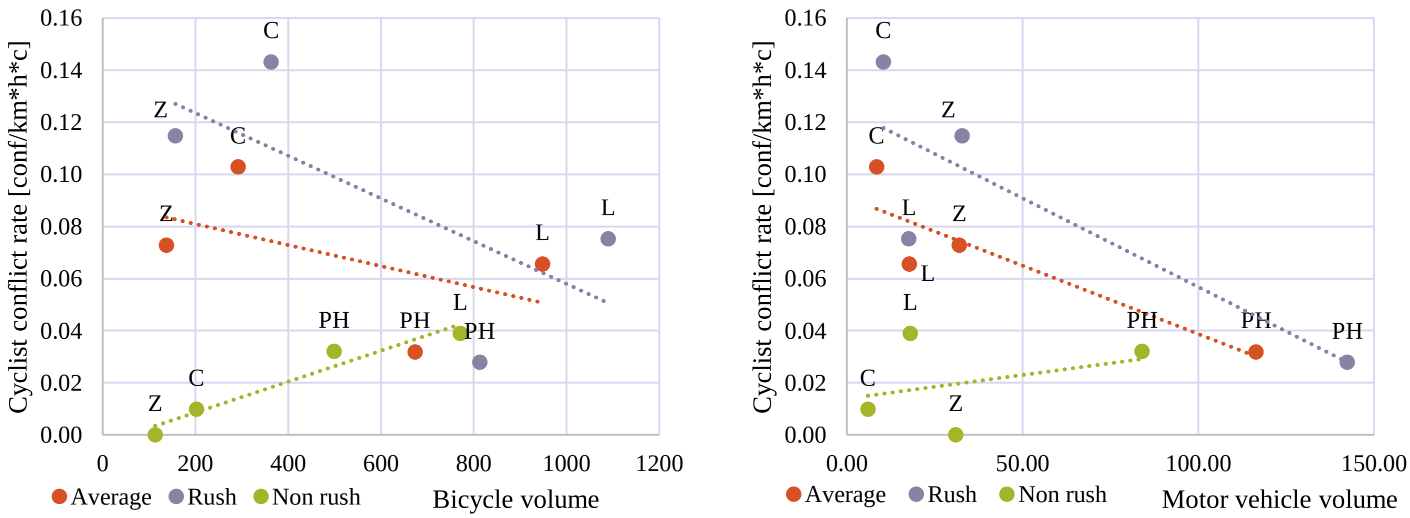


Figure 34 Cyclist conflict rates plotted against bicycle and motor vehicle volumes

7 Limitations and future directions

This section addresses the main limitations of the study in terms of data, scope and method and future directions of research on bicycle street safety. Firstly, this study uses crashes from the BRON dataset, of which under registration of crashes without motor vehicles, single-bicycle crashes, and crashes with light-to-no injuries is known. The effects of these limitations on the results of the comparison of crash cost rates of different facilities are expected to be minimal as the under registration is likely comparable amongst facilities. On the other hand, the possible imbalance in crash registration between municipalities may affect the outcomes as the ratio of facilities is not equal between municipalities. The low crash densities in Utrecht may results in a lower crash rate on bicycle streets, as over 50% of bicycle streets is located in this municipality. Within the study area also variations in bicycle volumes were found, where the bicycle volumes in Rotterdam are strongly overestimated, due to low participation of the FTW and placement of count locations at busy intersections. This results in an underestimation of crash rates on approximately 25% of non-bicycle street facilities and 5% of bicycle streets. The modelled motor vehicle volumes were comparable over the municipalities, however lacking data on bicycle streets required some rough assumptions that resulted in unreliable regression model outcomes. These data limitations highlight the importance of consistent data sources over the study area.

The network scope of this study was limited by the available traffic volume model estimations and the bicycle street registration in the Fietsersbond network. The limited number of bicycle streets prevented from disaggregating between bicycle street profiles (e.g. narrow street with rabat strips versus wider street with median), and possibly overlooking differences in safety and effects of traffic and environmental variables. Bicycle street road width has been found to significantly predict safety levels, together with traffic volumes, making this factor a valuable addition (van Boggelen & Hulshof, 2019).

Next, this safety comparison study is performed on the Dutch bicycle network, which is one of the more extensive and intensively used networks internationally. Making it difficult to extrapolate the results into an international context.

Lastly, some methodological issues are highlighted for the crash cost rate calculation and the conflict study. The crash rates are weighted by the crash severity but not by the number of involved cyclists. This might give different results as the conflict study showed that cyclists cycling in pairs are exposed to higher rates on bicycle streets, and higher numbers of bicycle-bicycle crashes are registered on bicycle streets. The conflict study is limited by the number of observation locations and the hours of video data collected. As an implication, only general concepts can be drawn from its results. With a larger scope, effects of road design (width, rabat strip, median) can be measured in more detail, and results can be validated. Furthermore, more objective measures of conflict (i.e. TTC (Hayward, 1972) and PET (Allen, Shin, & Cooper, 1978)) would benefit the reliability of the outcomes.

8 Conclusions

The aim of this study is to provide insight into the safety of bicycle streets, through a comparison of crash cost rates on bicycle streets and other bicycle facilities, and a conflict study on bicycle streets to more specifically address the characteristics of, and related factors to unsafe interactions. For this the following research questions were asked:

1. How do crash cost rates on bicycle streets compare with bicycle paths, bicycle lanes, and residential roads absent of a bicycle facility, at different time periods?

A crash cost rate was calculated for each segment in the bicycle networks (bicycle streets, bicycle lanes, bicycle paths, no facility roads) for four time periods based on: the amount of crashes on a link, the exposure at the time interval, the link length, and the social costs of the crash dependent on the severity level. The average crash cost rates on bicycle streets were found to be lower on bicycle paths, and comparable with the rates on bicycle lanes and regular residential roads.

2. How does the crash cost rate between bicycle streets and other facilities compare when controlling for external factors, and what is the relationship between cyclists' crash cost rate and these factors on different bicycle facilities?

In addition to the comparison of average crash cost rates, the rates were modelled with traffic, demographic, and socio-economic variables using the Tobit model. The all links model, in which the bicycle facility is a categorical variable with bicycle street as the reference, shows that cyclists on bicycle streets are exposed to higher crash rates than on any other bicycle facility. The bicycle street model shows that bicycle volumes are positively related to crash rates, while the relationship for motor vehicles is uncertain due to data limitations. In all models population density is positively associated with the crash cost rates. Furthermore, it is concluded that bicycle streets benefit traffic safety in low income areas, while they increase existing traffic safety inequalities between demographic groups.

3. How many conflicts occur on the selected bicycle streets, how can they be characterised, and what is their relation to traffic volumes?

A conflict study was performed on four bicycle streets, selected such that they vary on the main factors affecting near crash event occurrences on bicycle streets (motor vehicle and bicycle volumes, road width, and rabat strip width/median presence). 36 hours of conflict observation on four bicycle streets resulted in 1031 safe interactions and 71 conflicts (6.4%). In 82% of the motor vehicle involved conflicts (94%) the road space was sufficient and unsafe events were a result of: speeding (24%), cyclists not driving on the right hand side of the road lane (10%), and groups of cyclists causing hesitation in overtaking (17%). Motor vehicles and duo-cyclists were found to be much more frequently involved in conflicts than regular cyclists. The correlation tests between conflict frequencies and rates, and traffic volumes, contradict main perceptions that increased bicycle volume benefit cyclists' safety on bicycle streets. Lastly, it is suspected that bicycle streets with very low motor vehicle volumes do not properly facilitate interactions with motor vehicles, as they are designed to facilitate the high bicycle flow.

To conclude, this study adds to the knowledge gap on bicycle street safety by comparing objective safety levels to other bicycle facilities and analysing the "how" and "why" of unsafe events. It should be noted that these results are subject to some limitations in the crash and traffic volume data. However, the high average crash cost rates, and the regression model outcomes both show lower safety levels on bicycle streets. The conflict study provides characteristics of unsafe events and relationships between traffic volumes and unsafe events are identified. This study provides topics for future directions on bicycle street safety, and takeaways for policy makers and road designers for safer implementation of bicycle streets.

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9 Annex

This annex is an addition to the main report Analysis of cyclists' safety on "bicycle streets" and other facilities in four large Dutch municipalities: A crash and conflict study. Additional literature on bicycle street design, analyses methods and limitations of historical crash data, and traffic conflict techniques are included. Also, further information is provided on the characteristics of the bicycle streets in the network, and on the ADASYN method. The last section includes conflict study results related to bicycle street design.

9.1 Literature

9.1.1 Bicycle street design

Though not legalized, recommendations for bicycle streets in the Netherlands exist. This chapter addresses the changed perceptions on how bicycle streets should be designed for optimal performance, the ten design elements, and the Interaction predictor tool.

9.1.1.1 History of bicycle streets and design perceptions

Throughout the years, perceptions on how to facilitate large bicycle flows and access motor vehicle traffic on bicycle streets has varied. Table 12 summarizes the perceptions on design, requirements and applications of bicycle streets in the Netherlands from the first study (Andriesse & Hansen, 1996) to most recent design guidelines (CROW Fietsberaad, 2021). Andriesse & Hansen (1996) first defined the bicycle street as "a bicycle path, where motor vehicles are allowed in limited volumes". These bicycle streets were narrow (~3.85m) to discourage overtaking, and allowed only car traffic from one direction. In 2005 four types of bicycle street designs were introduced (Andriesse & Ligtermoet, 2005), two of which including rabat strips and/or a central reserve. Now, Dutch bicycle streets can be categorized into one of two designs (figure 35): 1) a narrow design with a single-lane and rabat strips at both sides, and 2) a wider design with two lanes separated by a (rounded) central reserve and possibly bordered by rabat strips.

Furthermore, the ratio of bicycle to motor vehicle volumes became an important design criterium, where the bicycle volume should be two to four times larger. 15 years later, the perception on this changed, where well-functioning bicycle streets also exist with ratios of 1/1 and even 0.5/1 (van Boggelen & Hulshof, 2019).

Table 12 Bicycle street perceptions throughout the years, on design, recommendations/guidelines and applications

	Bicycle street definition	Road width	Rabat strip	Central reserve	Traffic volumes
Andriesse & Hansen (1996)	A street that is designed as a bicycle path, where motor vehicles are allowed in limited volumes.	3.85m	NA	NA	Max 600 b/h and 400 mv/h with negative exponential relation
Andriesse & Ligtermoet (2005)	A street within a residential area that functions as an important bicycle route, is recognizable through the design, where motor vehicles are allowed in limited volumes, and cars are subordinate to bicycles.	3.5-4.5m	0.6m Max 1.10m	Flexible	Ratio b/mv volume: 2 to 4 time more cyclists
Andriesse & van Boggelen (2016)	A road design type where two functions are combined, i.e. thoroughfare for bicycle traffic and property access for motor vehicle traffic.	I) 3-4.8m II) 4.5-7m	Max 0.5m	0.5-1.5m	Ratio b/mv volume: 1/1 or even 0.5/1
van Boggelen & Hulshof (2019)		4.2-7.1m	0.3m		

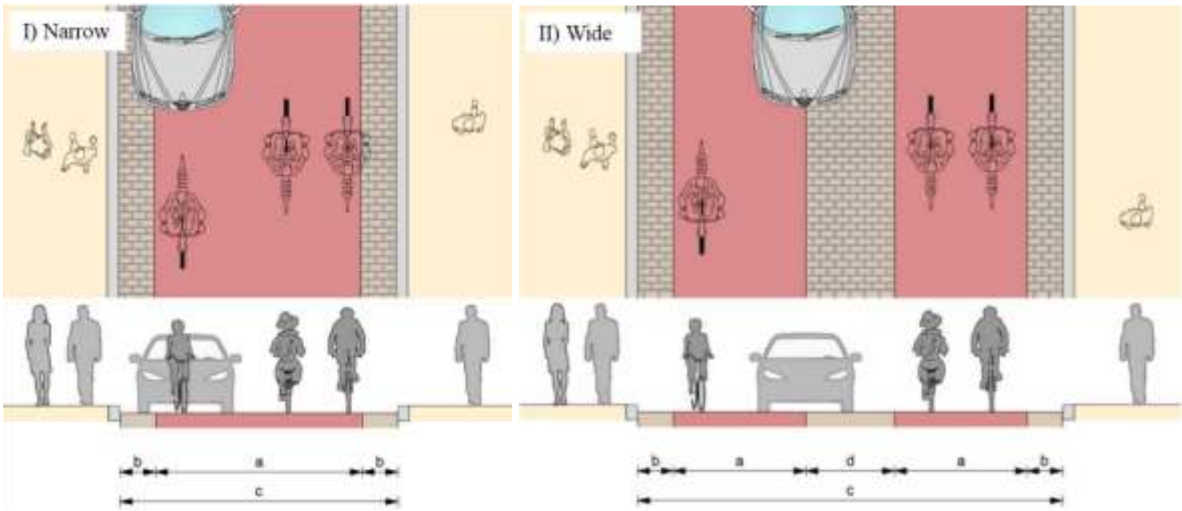

Figure 35 Two basic bicycle street designs: I) Narrow (3 - 4.8m) and II) wide (4.5 - 7m) from (Andriesse & van Boggelen, 2016)

9.1.1.2 *Ten design elements*

The existing design recommendations for Dutch bicycle streets are noted in the ASVV (*Aanbeveling voor Stedelijke Verkeersvoorzieningen;* Recommendations for urban transportation facilities). Based on the CROW studies Andriesse & van Boggelen (2016) and van Boggelen & Hulshof (2019) ten design elements are recommended in the ASVV (*Essential design elements):

1. Road width is in line with car and bicycle volumes*.
2. Road layout highlights both the through-cycling and car-access character:
    a. Rabat strips on both sides (0.3m);
    b. Road lanes with bicycle path/lane width;
    c. Possibly a median (0.5 to 1.5m);
    d. No length markings.
3. Pavement highlights both the through-cycling and car-access character:
    a. Road lanes: Red or red-like asphalt*;
    b. Rabat and median: cobbles, evenly and tightly paved.
4. Signage and symbols: *Fietsstraatbord L51** (figure 36).
5. Low speed for motor vehicle traffic guaranteed: when necessary sinus-shaped 30 km-speed bumps.
6. Traffic circulation measures: when necessary (alternating) one-direction traffic for motor vehicles.
7. Intersections with access roads: priority intersection with continuous profile.
8. No parking, (un)loading, or kiss&ride on the road; possible facility in the driving direction.
9. Avoid conflicts with pedestrians: sidewalk(s) and possibly crossing facilities.
10. Street light, trees, and other vertical elements can enhance both the car-access and through-cycling function.

Figure 36 Bicycle street sign (Fietsstraatbord L51)

The implementation of the three essential design elements ensures that the bicycle street is of sufficient quality and recognizable to road users. This includes, first and foremost, a road width that is in line with the traffic volumes, but also red pavement and the *Fietsstraat* sign. From table 13 the optimum road width can be obtained based on known bicycle and motor vehicle volumes. Depending on the traffic volumes, different vehicle combinations are guiding. The road width includes two rabat strips of 0.3m. Also, 10% of cyclists are assumed to be duo-cyclists.

Table 13 Recommended road width selection per motor vehicle and bicycle volume. From van Boggelen & Hulshof (2019) with author edits

	Two-directional			One-directional		
	Cyclists/h					
MV/h	100	200	400	100	200	400
50	450	450	450	420	420	450
100	500	480	480	420	420	450
150	590	510	480	510	420	450
200	630	590	480	510	510	450
250	No bicycle street*	630	510	No bicycle street*	510	510
300		630	590		590	590
350		710	630		590	590
400					590	590

Guiding vehicle combination

C-C	C-MV-(C)	MV-MV

**possibly bicycle lanes with narrow road lane*

Based on the road width, the profile is selected following figure 37. The two alternative bicycle street profiles are the narrow and the wide design (figure 35). With a road width of over 6.5m there is the option of bicycle lanes with a narrow MV road lane. In the considerations the desired dwelling function can be taken into account, where bicycle streets service this more.

The two bicycle street profiles differ strongly in the behaviour they enforce. On the single lane street cyclists are forced to take a more prominent position, and as a result enforcing motorized vehicles to anticipate on cyclists. On the two-lane bicycle streets cyclists drive more at the right hand side of the carriageway, allowing motorists easier passage.

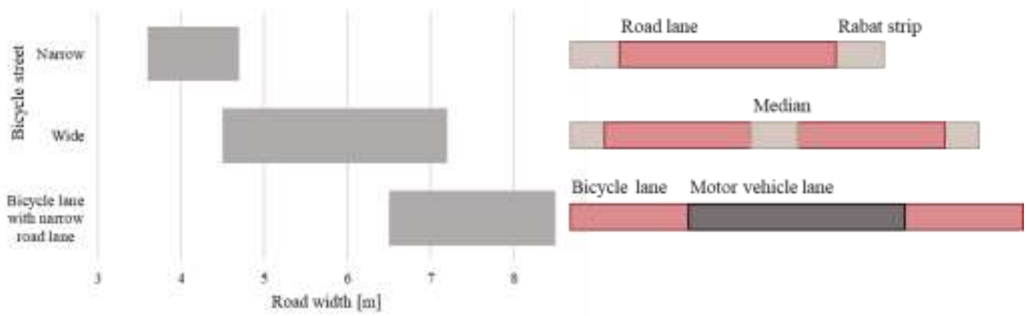

Figure 37 Desired road profile of bicycle street per road width. From van Boggelen & Hulshof (2019) with author edits

In addition to the essential design elements, the rabat strip, median, speed reduction measures, driving directions and parking also effect bicycle street performance. The rabat strip forces cyclists to position themselves in the middle of the road, and thus dominating the road space over cars. This effect is what distinguishes the bicycle street from bicycle paths and lanes. Recommendations for the rabat strip width have changed from wide (0.6m) to more narrow strips (max 0.5m to 0.3m). Reasoning for this has been that in practice wide rabat strips take away road lane space, forcing cyclists to use the uncomfortable strip in case of interaction with a car.

Similarly to rabat strips, the median also highlights the dwelling function of the street. The median cautions motor vehicle drivers about entering the opposite road lane when overtaking. However, Delbressine (2013) did not find that the median indeed withheld car drivers from overtaking cyclists.

A speed limit of 30 km/h is a fundamental condition for safe bicycle streets. A low speed limit is desired following the (bio)mechanics principle of Sustainable Safety (SWOV, 2018). Wide bicycle streets are (weakly) associated with higher motor vehicle speeds (Delbressine, 2013). However, reducing the road width has shown to lead to more bothersome/dangerous interactions (van Boggelen & Hulshof, 2019). Other literature suggests measures to reduce motor vehicle speeds, such as speed tables, coloured surfaces, and setting lower speed limits (Walker, Tresidder, Birk, Weigand, & Dill, 2009). A study on Swedish bicycle streets showed that a speed limit reduction from 30 km/h to 20 km/h, reduced actual speed to on average 25 km/h (Denvall & Johansson, 2013).

In case of too little space for the recommended road width (based on volumes), partial and alternating one-direction car traffic can be a solution. Restricting motor vehicles from one direction leads to a reduction in bothersome/dangerous interactions, even if the volumes remain equal. One-directional traffic can thus be used as a tool, but is not the norm.

Finally, road side parking is inherent to access roads. However, parking and stopping on the road may decrease safety and comfort for cyclists. These events should be minimized where possible. If parking along the street is necessary, the preferred form is parallel parking, over perpendicular or diagonal parking. The recommended width for parking spots of 2.2 to 2.5m to prevent impairment of the effective road space.

9.1.1.3 Interactions predictor tool for bicycle street design

In addition to the ten design elements for bicycle streets, van Boggelen & Hulshof (2019) also developed a tool to aid municipalities and engineers in designing a well functioning bicycle street based on the traffic volumes. The *Ontmoetingenvoorspeller* (Interaction predictor) is a tool for the design of streets with mixed traffic (DTV-Consultants, 2019), and is based on study findings of conflicts observations on 8 bicycle streets and 3 streets with bicycle lanes (Godefrooij & Hulshof, 2017). The tool consists of two steps: 1) determine how often vehicle combinations/interactions occur based on traffic intensities, and 2) determine the required road width based on the predicted interactions. The required road width is based on the minimum space between cyclist and objects for safe and comfortable travel (figure 38) and on the widths and passing distances of and between road users (CROW fietsberaad, 2016).

9.1.2 Analysis with historic crash data

In traffic safety studies, various definitions are used to quantify safety, i.e. crash counts, crash rates, and crash risk. Several studies evaluated traffic safety based only on crash occurrences or counts at a location or per km road length (Wachtel & Lewison, 1994; Jensen, Rosenkilde, & Jensen, 2006; Pedroso, Angriman, Bellows, & Taylor, 2016). This primary method neglects the exposure and the severity of crashes. Exposure and risk are two primary dimensions in safety analysis that address these limitations. Exposure can be defined as the condition of being affected by something or being at risk of involvement. In traffic safety, exposure is often expressed as traffic volumes and is needed to allow comparison of crashes at different locations or moments in time (Vanparijs, Panis, Meeusen, & de Geus, 2015). The crash rate is the ratio between the number of crashes (i.e., crash count) and traffic volumes (i.e., exposure).

Next, risk is the probability of having a crash given a certain amount of exposure, together with the consequences are the injury level provided a collision occurs, i.e., property damage, slight or severe injury, and fatality (Wegman, Zhang, & Dijkstra, 2012). Crash risk is frequently used in traffic safety studies as it is encompasses the main aspects of safety (e.g. Vandenbulcke et al. (2009) and Kocatepe et al. (2019)). Furthermore, some studies include multiple safety quantifications in their analyses (Tesche, et al., 2012; Chen & Shen, 2016; Myhrmann, Janstrup, Moller, & Mabit, 2021). This study adopts an alternative to crash risk by weighting the crash rates by the associated social costs of the severity level of the crash, resulting in a crash cost rate.

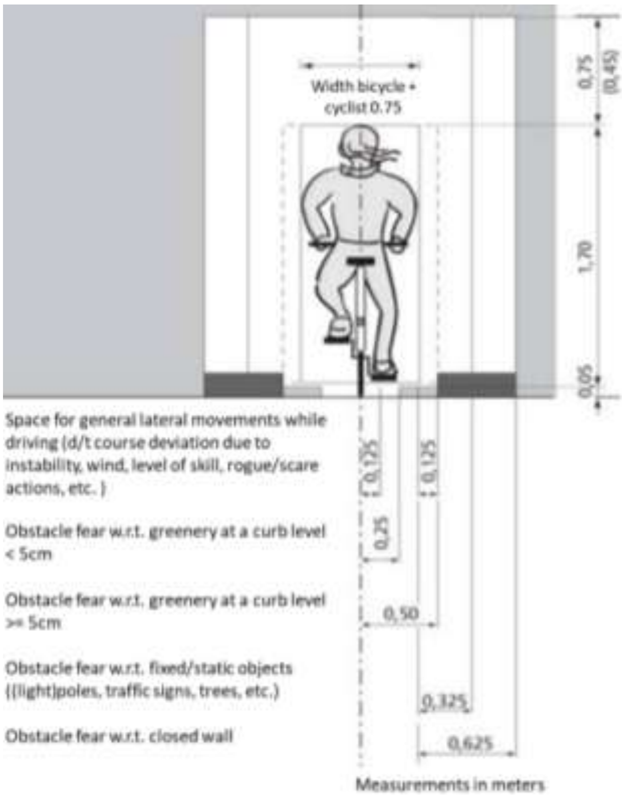

Figure 38 Profile of cyclist space, obtained and translated from the design guidelines of bicycle traffic (CROW fietsberaad, 2016)

Whether estimating crash counts, rates or risks, such crash data studies always rely on registered historic crashes. This data mostly originates from police crash reports. Other sources are hospital and ambulance records and insurance claims. However, police registered crash databases are known to suffer from underreporting bicycle crashes, especially crashes without motor vehicles and crashes with less severe injuries (SWOV, 2017). A variety of studies addressed the underreporting of bicycle crashes, as it may lead to inaccurate evaluation of crash risks and thus under- or overestimation of traffic safety situations (Doggett, Ragland, & Felschundneff, 2018). For example, from 2000-2009 in the Netherlands, according to police data, the number of serious injuries decreased by 36%, whereas hospital data showed an increase of 35% (OECD/ITF, 2013).

Table 14 summarizes the main findings on the completeness of different types of crash databases. These values are obtained by capture-recapture methods and comparisons with self-reported injury data from surveys. Overall it can be concluded that bicycle crashes are severely underreported in all databases. However, linking databases provides a more complete collection of crashes, as each database has its strengths and weaknesses. For example, hospital reports include more single-bicycle crashes and crashes with slight injuries (Moller, Janstrup, & Pilegaard, 2021). In contrast, police and insurance records are more geographically specific (Winters & Branion-Calles, 2017) and provide information on the crash environment.

Table 14 Completeness of crash databases, % of bicycle crashes reported.

		Police	Hospital	Insurance	Linked police & hospital	General reports
Total		11%[1]	22% [3] 45% [1]	12% [4]	73.7% [5]	10% (Denmark) [1]
Severity level	Fatal					~100% [2]
	Severe injury	30% [2] (NL)			40% [2] 14% (Denmark) [6]	
	Slight injury	10.5% [1] 4% [2]	57.3% [1]		12% [7] 7% (Denmark) [6] 10% [2]	
Crash type	B-MV	25% [2]			80% [7] 54% [3]	
	B-any				22% [3]	
	B-B	10% [2]				
	Single-B	3.3% [1]	54.4% [1]			0-8% [8]

[1] Moller et al. (2021); [2] Shanar et al. (2018); [3] Langley et al. (2003); [4] Winters & Branion-Calles (2017); [5] Tin Tin et al. (2013); [6] Janstrup et al. (2016); [7] Dhillon et al. (2001); [8] Elvik & Mysen (1999)

9.1.3 Traffic conflict techniques

Traffic conflict techniques (TCT) originate from the need for an alternative to the traditional approach of using historical accident data. The historical accident data method is often critiqued as it is reactive (Stipancic, Zangenehpour, Miranda-Moreno, Saunier, & Granié, 2016), long periods of data collection are needed due to the scarcity of collisions (Sayed, Zaki, & Autey, 2013), and crash data is often of poor quality. TCTs can be used to give insight into potential safety problems, and should not be used to provide accident estimates (Brown & Cooper, 1990; Gstalter & Fastenmeier, 2007).

The concept of Traffic Conflict Techniques (TCTs) was first introduced by Perkins and Harris (1967), who argued that systematically observing traffic conflicts would obtain much more comprehensive information on traffic safety than historical accident data could. Next, Hayward (1972) and Allen et al. (1978) added new techniques to measure traffic conflicts. Time-to-Collision (TTC) became the first physically measurable unit for a clear definition of (dangerous) conflicts. TTC is a continuous time measure from two vehicles that are on a collision course until the occurrence of collision (figure 39) (Hayward, 1972). TTC requires two road users to be on a collision course, meaning no conflict is registered when collision courses are avoided by even a fraction of a second. TTC is currently widely applied in combination with automated video analysis in which trajectories are tracked and analysed (Saunier, Sayed, & Ismail, 2010; Sayed, Zaki, & Autey, 2013).

Allen et al. (1978) rejected the assumption of Perkins and Harris (1967) that a traffic conflict can be defined based on visible evasive actions or the occurrence of traffic violations. They developed a more comprehensive conflict measurement technique: post-encroachment time (PET). PET is the time between the moment that the first road user leaves the course of the second and the second reaches the course of the first (figure 40). Similar to TTC, PET is dependent on crossing trajectories. As a result, PET has been applied primarily in conflict studies at intersections (Stipancic, Zangenehpour, Miranda-Moreno, Saunier, & Granié, 2016; Zangenehpour, Strauss, Miranda-Moreno, & Saunier, 2016). TCTs were initially developed for motor vehicle interactions, but post-encroachment-time has also been successfully used to assess interactions in non-motorized space (Beitel, Stipancic, Manaugh, & Miranda-Moreno, 2018).

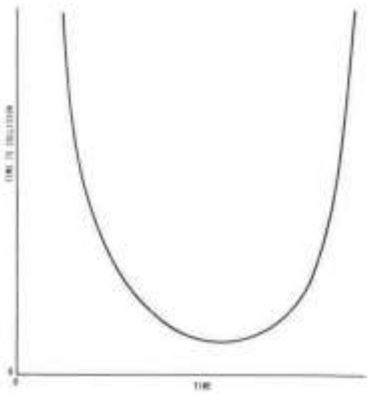

Figure 39 Theoretical curve of TTC, from Hayward (1972)

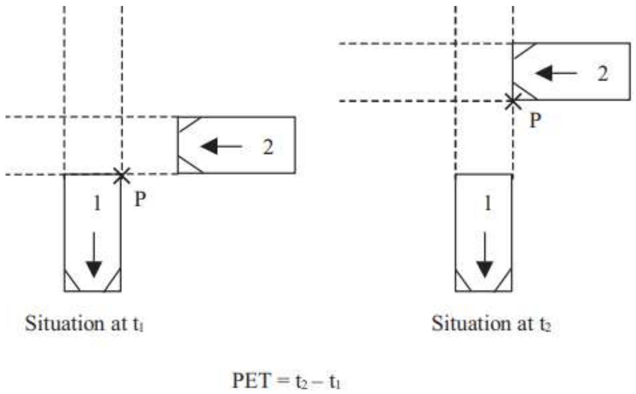

Figure 40 Definition of Post-encroachment time (PET), from van der Horst et al. (2014)

With the introduction of TCTs, the existence of a correlation between conflicts and crash occurrence was simply assumed. However, critics argue that TCTs only provide an abstract representation of unsafety and lack a formal link to observed crashes. Williams (1981) concluded that the relationship between conflict and accidents was, at the time, not proven beyond a reasonable doubt, and accepted based on its face validity. Over the years, research on the correlation between traffic conflicts and accidents have given different results (Zheng, 2014). It should be noted that the ongoing issue of underreporting and poor data quality significantly impacts the possible correlation. On the contrary, some argue that the need for this validity is exaggerated. They believe that TCTs do not provide accident estimates but give insight into potential safety problems (Brown & Cooper, 1990; Gstalter & Fastenmeier, 2007). Despite the lack of proven validity, the conflict method is accepted for traffic safety studies, especially when historical crash data is of limited quality.

9.1.4 Crash data and traffic conflict studies

The previous two subsections addressed two main approaches to quantifying and analysing traffic safety: historical crash data analysis, and traffic conflict techniques. Both conflicts and crashes are part of the same crash generation process in which conflicts may evolve into crashes depending on an (un)successful evasive action (Allen, Shin, & Cooper, 1978). Figure 41 shows how conflicts always precede crashes, but a direct relation between the two, in terms of a crash-to-conflict ratio, has not been found (yet) (Zheng, 2014).

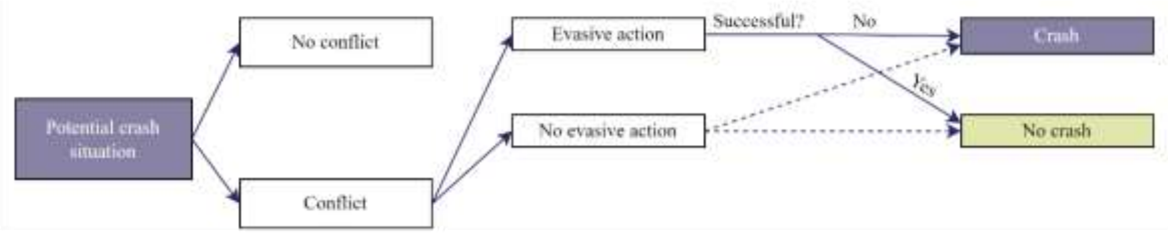

Figure 41 Crash generation process, based on Allen et al. (1978)

Figure 42 shows how traffic safety can thus be explained by both crash occurrences and severities, and (less directly) by severe conflicts. Both crashes and conflicts originate from the same set of observable user position, behavioural, and external factors. The success of an evasive action, the original road user trajectories, travel speeds, and the road users' position determine whether a potential crash situation develops into a slight/severe conflict or a crash. Other factors that play a role, but are less measurable, are the age and agility of road users, attitude, and the arbitrarity of crash outcomes.

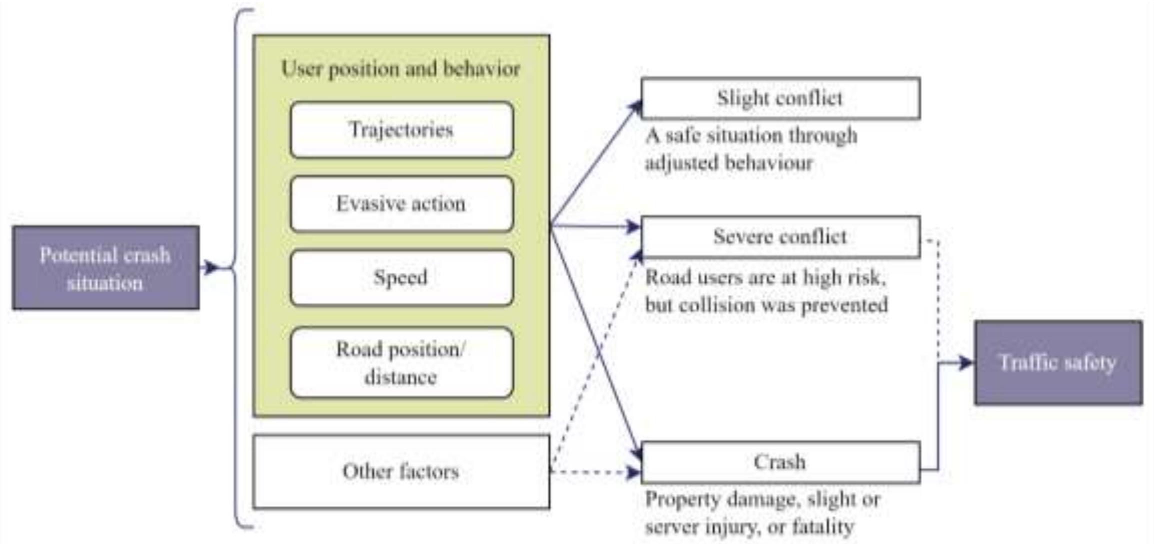

Figure 42 Traffic safety indicated by crashes and severe conflicts, depending on the same set of underlying factors

9.2 Additions to data and methodology

In this chapter, additional information on the bicycle street in the crash analysis network, and on the ADASYN method are provided.

9.2.1 Bicycle streets in the network

The location of bicycle streets is based on their notation in the *Fietsersbond* network (Dutch Bicycle Union, 2020), and a manual check for the set criteria. In the dataset, 69 streets were noted as a bicycle streets. Four of those were found to actually be (in 2021) roads with bicycle lanes, and five were bicycle paths (i.e. not accessible by car) (a total of 13%).

Additionally, seventeen (25%) more streets are excluded from the study as they do not meet the required design elements: 1) the street is accessible for both cyclists and motor vehicles, and 2) it has at least one of the following design elements: red pavement, a rabat strip or a central reserve. Municipalities may have labelled these streets as bicycle streets but the set criteria for this study were lacking. In The Hague, 38% of the bicycle streets were such false bicycle streets. Percentages are slightly lower in Utrecht and Amsterdam (respectively 31% and 27%), and no false bicycle street were found in Rotterdam. The exclusion of these streets resulted in a final 43 bicycle streets (62%), combining to 28.61 km (Appendix E). 15.56 km is located in the municipality of Utrecht.

Figure 43 shows some design descriptives of the bicycle streets included in the crash cost rate analysis (details in Appendix F). 83% of the streets has parallel parking on one or more sides. The majority of streets do not have a central reserve. 50% of bicycle street with a central reserve also have rabat strips. Rabat strips and medians are mostly paved with cobbles.

As there are no national legalised design guidelines, and most bicycle streets were constructed before the CROW publication on design handles for bicycle streets (Andriesse & van Boggelen, 2016), municipalities have constructed streets following their own perspectives. For example, streets with central reserves are only found in Utrecht and Rotterdam (as in figure 44.d), whereas central lines are most common in The Hague (as in figure 44.b)

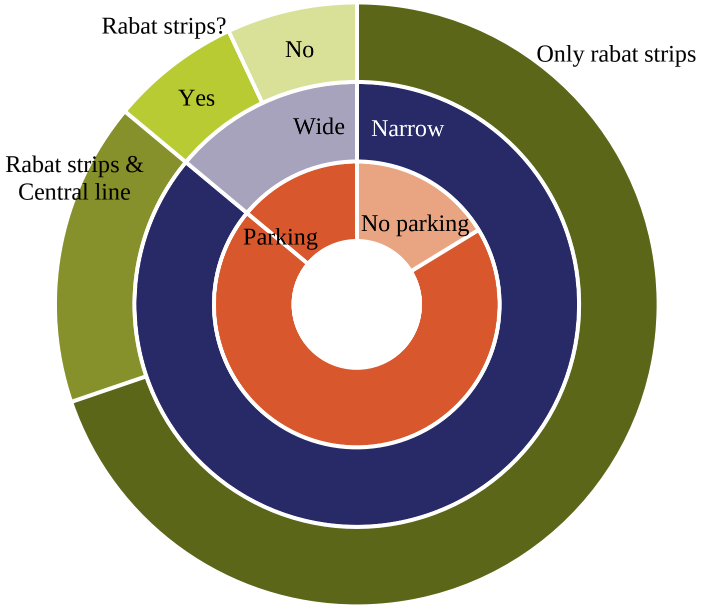

Figure 43 Overview bicycle street design characteristics, obtained from Cyclomedia (2022)

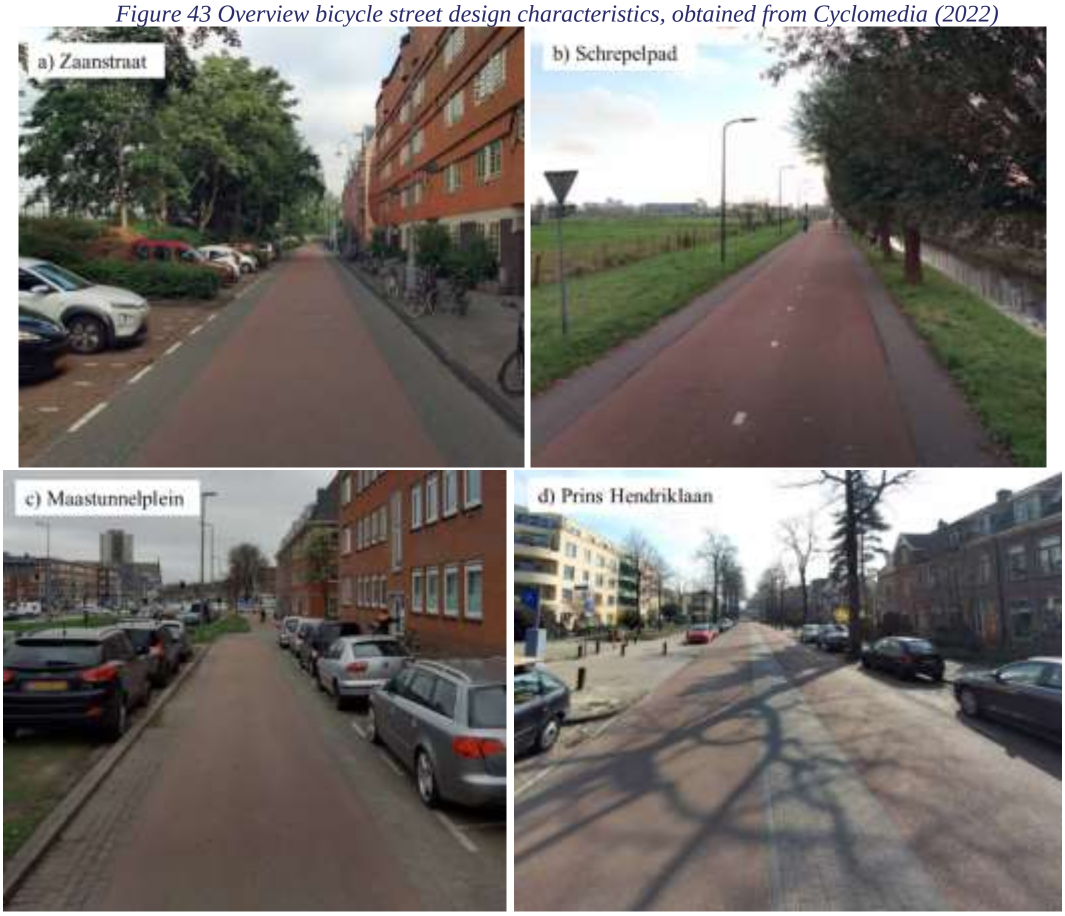

Figure 44 Bicycle street design examples: a) Zaanstraat (Amsterdam), b) Schrepelpad (The Hague), c) Maastunnelplein (Rotterdam), d) Prins Hendriklaan (Utrecht) (Cyclomedia, 2022)

9.2.2 ADASYN: effects of K and β

ADASYN is a synthetic data generation tool that can be used to over-sample the minority class (He, Bai, Garcia, & Li, 2008). In other words, new data points are generated to complement the existing minority class. An important characteristic is that with ADASYN the number of observations created around a minority point depends on the impurity ratio of that minority point. This ratio is calculated for each minority point x_i, with K neighbours (Equation 6). A high impurity ratio results from a high number of neighbours in the majority class Δ_i. Next, the impurity ratio is normalized to create a density function (Equation 7). The number of synthetic data points to be generated results from Equations 8 and 9, where G depends on the desired balance level β, and m_s and m_l are the minority and majority classes respectively (Equation 10).

$$r_i = {}^{\Delta_i}/_{K} \qquad (6)$$

$$\hat{r_i} = \frac{r_i}{\sum_{i=1}^{m_s} r_i} \qquad (7)$$

$$g_i = \hat{r_i} \times G \qquad (8)$$

$$G = (m_l - m_s)\beta \qquad (9)$$

Then the synthetic data points are generated by Equation 10, with x_{zi} a randomly chosen minority data point from K nearest neighbours of x_i, and a random number λ [0,1].

$$s_i = x_i + (x_{zi} - x_i) \times \lambda \qquad (10)$$

The variables K and β influence the weight of the minority outlier points and the number of synthetic points generated, respectively. These values should be carefully selected to maintain the integrity of the original data. The K value represents the neighbourhood from which the impurity ratio is calculated. Figure 45 provides two examples at $K = 10$ and $K = 30$ for the impurity ratios calculated for a random minority point (triangle). The impurity ratios r_i are normalized to create a density function that makes ADASYN adaptive. Following this density function, more points are generated around outlier points to make them easier to model. The weight of these outliers reduces when the K value increases as for $K \to \infty$, $\hat{r_i} = \frac{1}{m_s}$.

More balanced impurity ratios result in less points around outliers, and generated points regression towards the mean. The latter can be explained by the point generation process, in which the data point is located at the relative distance λ, between minority point x_i and a randomly selected minority point x_{zi} inside its neighbourhood (figure 46). With a large K value the probability that the selected point is inside a minority cluster increases and values regress to the mean.

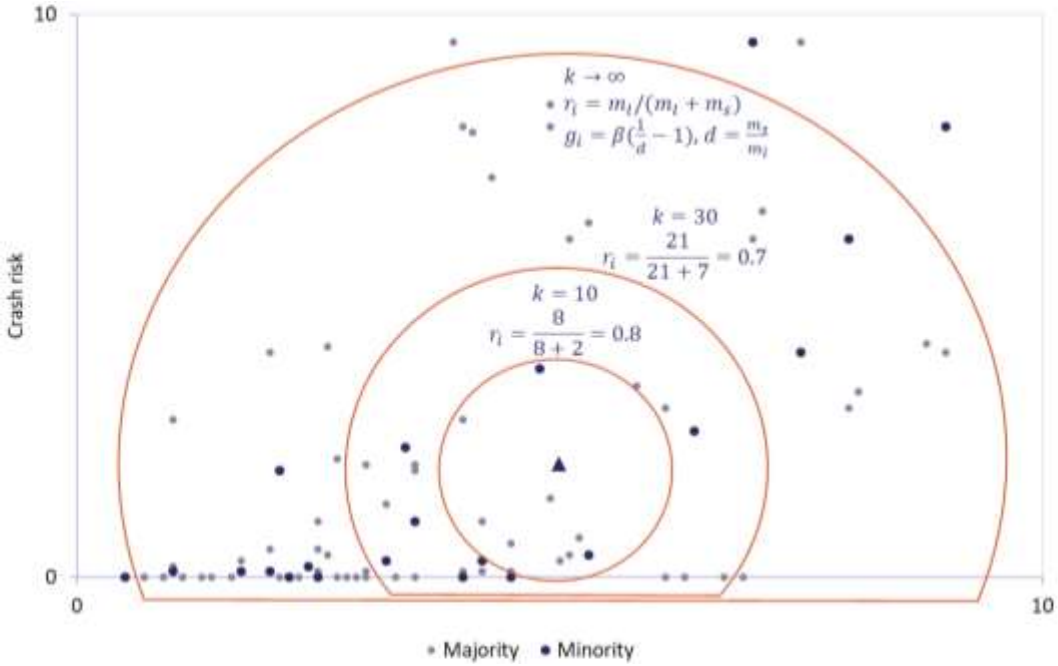

Figure 45 K neighbourhood example for crash rate-like datapoints

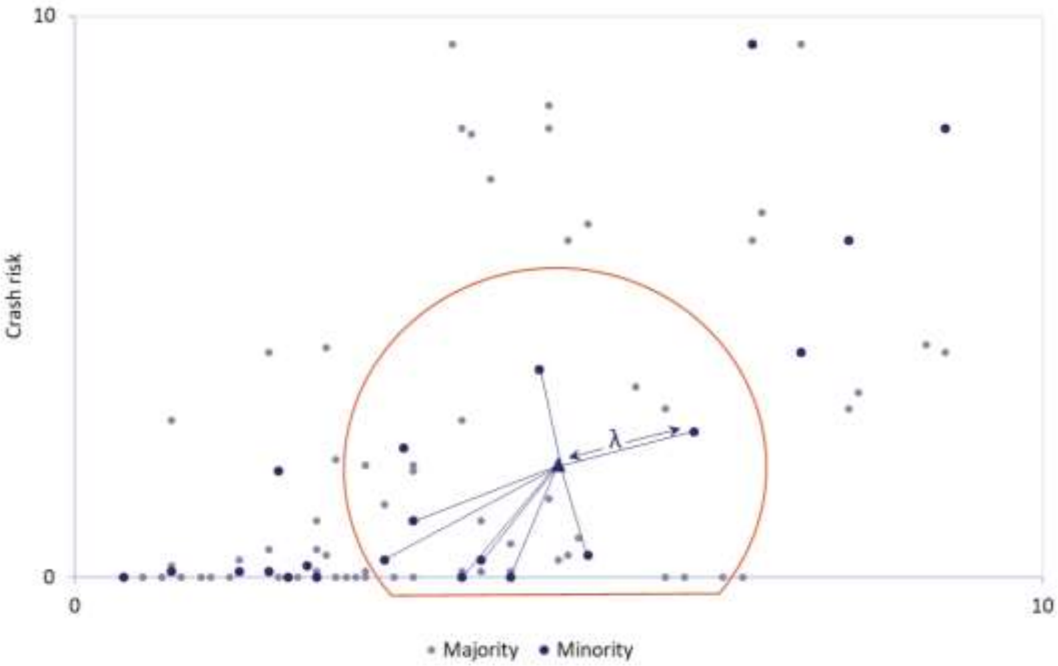

Figure 46 Synthetic data point generation example

Figure 47 shows the deviation between the original data means and the resample data means for all variables. It can be seen that crash rate mean is strongly influenced by the neighbourhood size, as ~80% of the datapoints is censored at zero. With a $K > 20$ the crash rate mean drops below the original mean. This happens as with a large K value the majority of datapoints is generated within the clusters (rate = 0), which lie in this case slightly below the mean (rate ≈ 80).

Next, the sensitivity of the regression coefficients to the K value was tested (figure 48). The standardized coefficients of the categorical variables increase by a factor two-to-eighteen when using resampled data. Thus, the resampling of crash-based data aids in the significance of regression outcomes but reduces the reliability of the coefficient sizes.

The value $K = 20$ was selected such that the deviation from the variable means and coefficients of the original dataset are minimal. The total number of generated points depends on the desired balance level β and the difference between the majority and minority classes. Figure 49 shows that the variable means have a minimal sensitivity to β. Therefore, β is selected such that the ratio of resampled data is minimal, while the model performance (significance of coefficients) is optimal. Following table 15, $\beta = 0.05$ is selected. The variables Median income level, population factor (0-15, 15-25, and 25-45), and MXI were not significant in any of the models. It should be noted that without resampling, the crash cost rate differences between bicycle streets, and bicycle lanes and paths are not significant.

Figure 51 shows how the number of generated points G at a $\beta = 0.05$ is a fraction of the majority group (bicycle path) but doubles the number of bicycle street observations.

*Table 15 Day average Tobit regression model p-value outcomes per β, with *** p < 0.001; ** p < 0.01; * p < 0.05*

	β = 0.00	β = 0.02	β = 0.05	β = 0.1	β = 0.25	β = 0.5
Intercept	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***
MVV	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***
FacilityxBL	0,8170,	0,4650,	≈0, ***	≈0, ***	≈0, ***	≈0, ***
FacilityxBP	0,0765,	0,0154, *	≈0, ***	≈0, ***	≈0, ***	≈0, ***
FacilityxNF	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***
Pop D	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***
PF 45-65	≈0, ***	≈0, ***	0,0026, **	0,0027, **	0,0328, *	0,0471, *
PF 65+	0,0292, *	0,0297, *	0,0127, *	0,0150, *	0,0034, **	≈0, ***
SPL	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***	≈0, ***

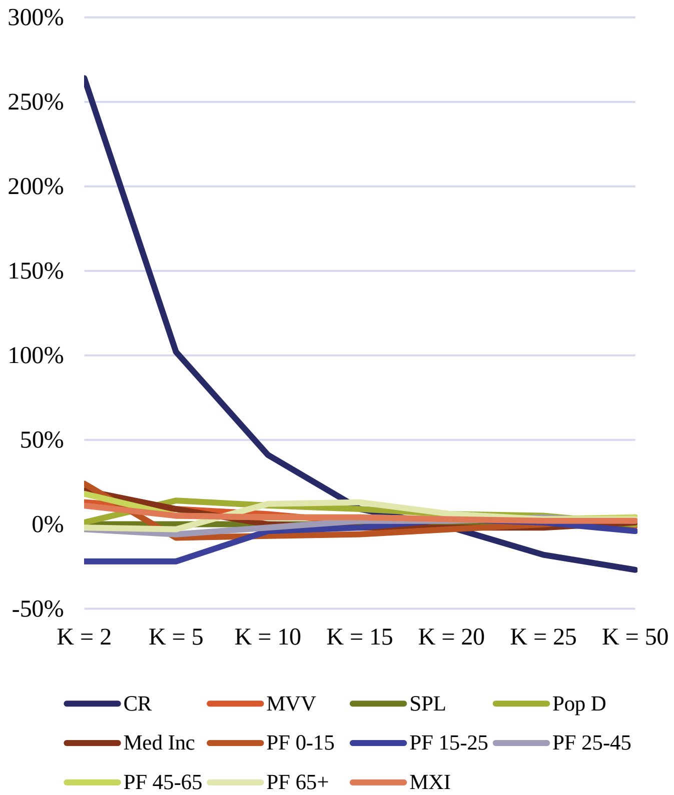

Figure 47 Differences variable means: resampled versus original data, per K for β = 0.05

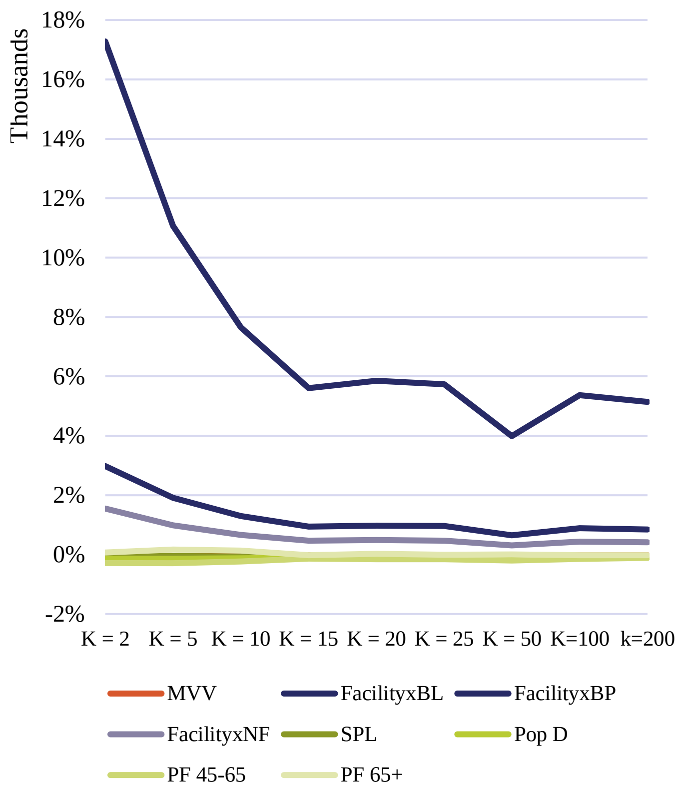

Figure 48 Differences regression coefficients: resampled versus original data, per K for β = 0.05

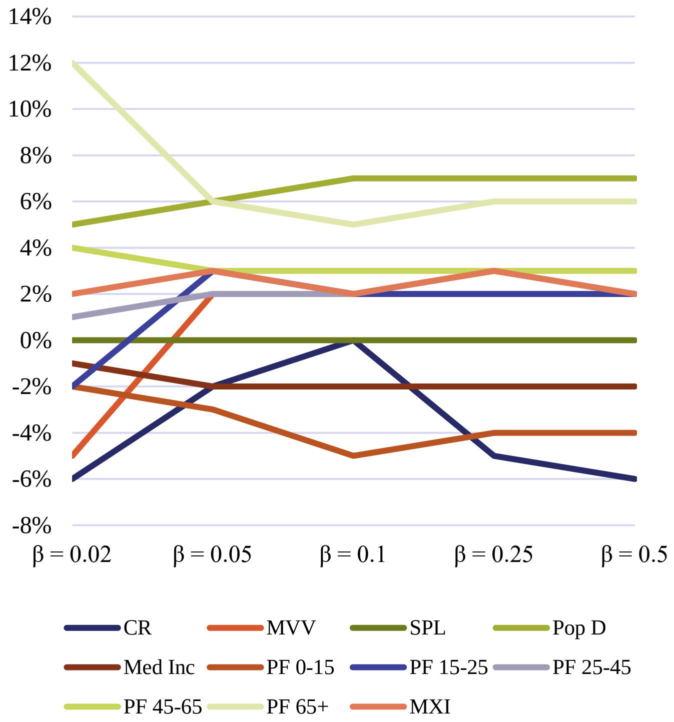

Figure 49 Differences variable means: resampled versus original data, per β for K = 20

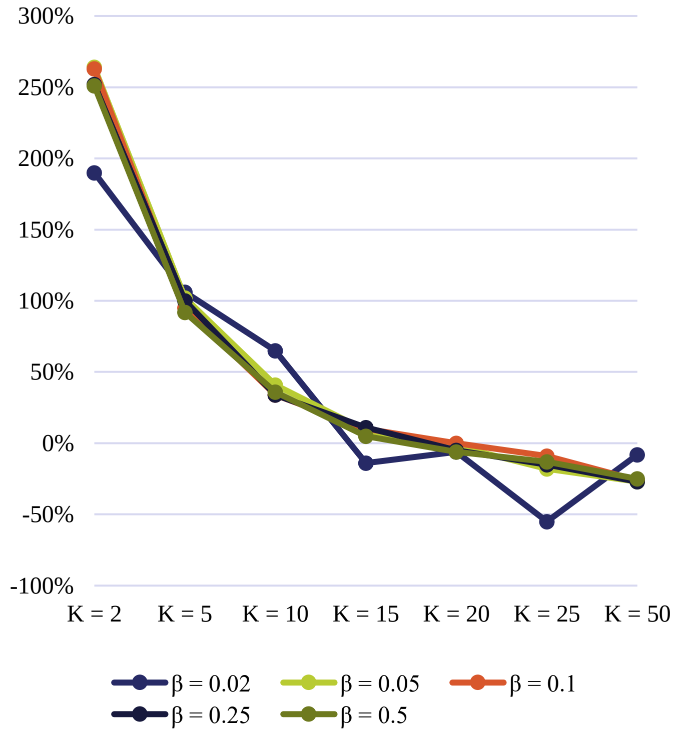

Figure 50 Differences crash rate means: resampled versus original data, per β per K

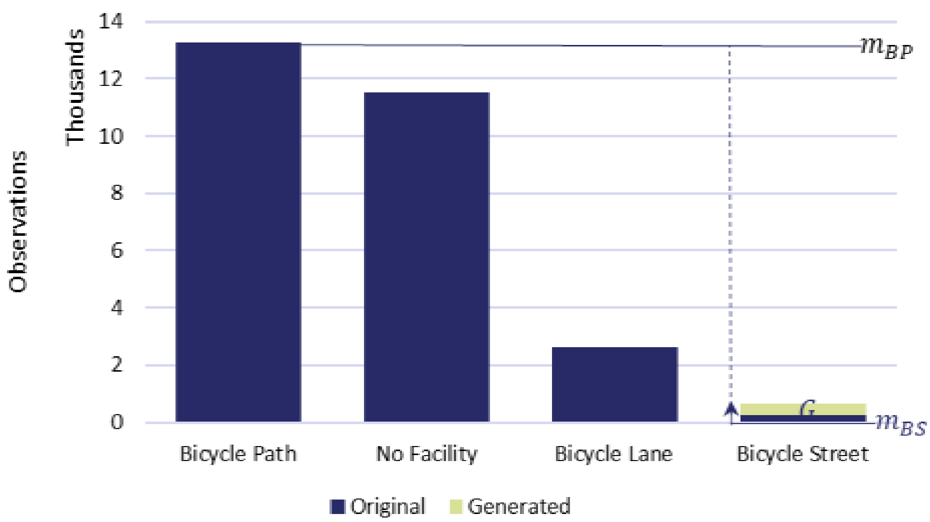

Figure 51 Synthetically generated points G with $\beta = 0.05$

9.2.3 Descriptive statistics of synthetically generated data

The synthetic generation of data points using the adaptive weighting method aids in modelling of the "harder to understand" events. Thus, the generated data points are likely to be skewed away from the average original values. Appendix A proves the data descriptives of the original bicycle street variables and the resampled variables. Below some remarks are made on the effects of resampling on the structure of the data.

Firstly, the standard deviations of the resampled variables are smaller than the original variables. As the generated data points are randomly located between two points of the minority class (figure 52), the generated points are located closer to the (new) mean. Furthermore, since mostly outliers are generated, the new mean shifts towards these outliers. Figure 53 shows that the generated points contain relatively more non-zero crash points than the original dataset. For the bicycle street crash rate variable, this means the number of censored values reduces from 78% to 66%.

Furthermore, the resampled data has lower average bicycle volumes, and higher average motor vehicle volumes. Meaning that relatively more "bicycle streets" are created with low bicycle and high motor vehicle volumes (figure 53, top left quartile). This graph also highlights (with the blue arrow) how generated points are limited to lie between two existing points.

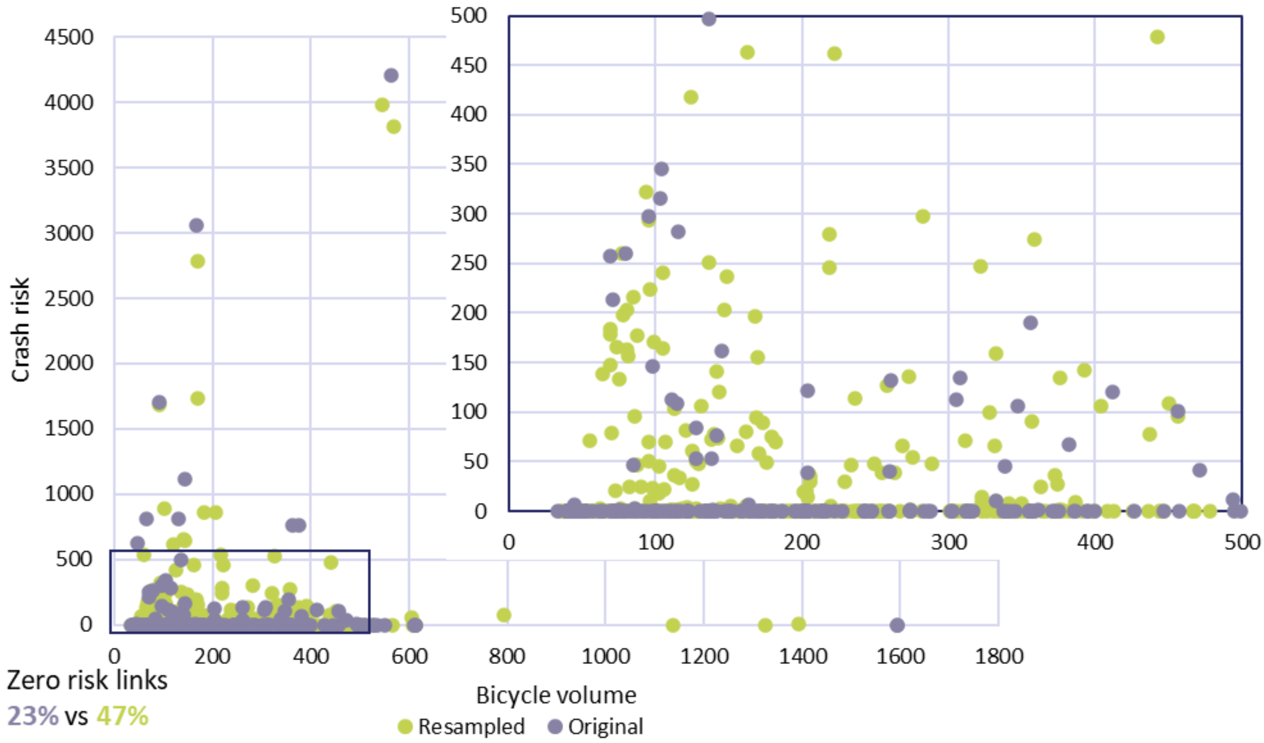

Figure 52 Example plot of original and resampled bicycle street data points

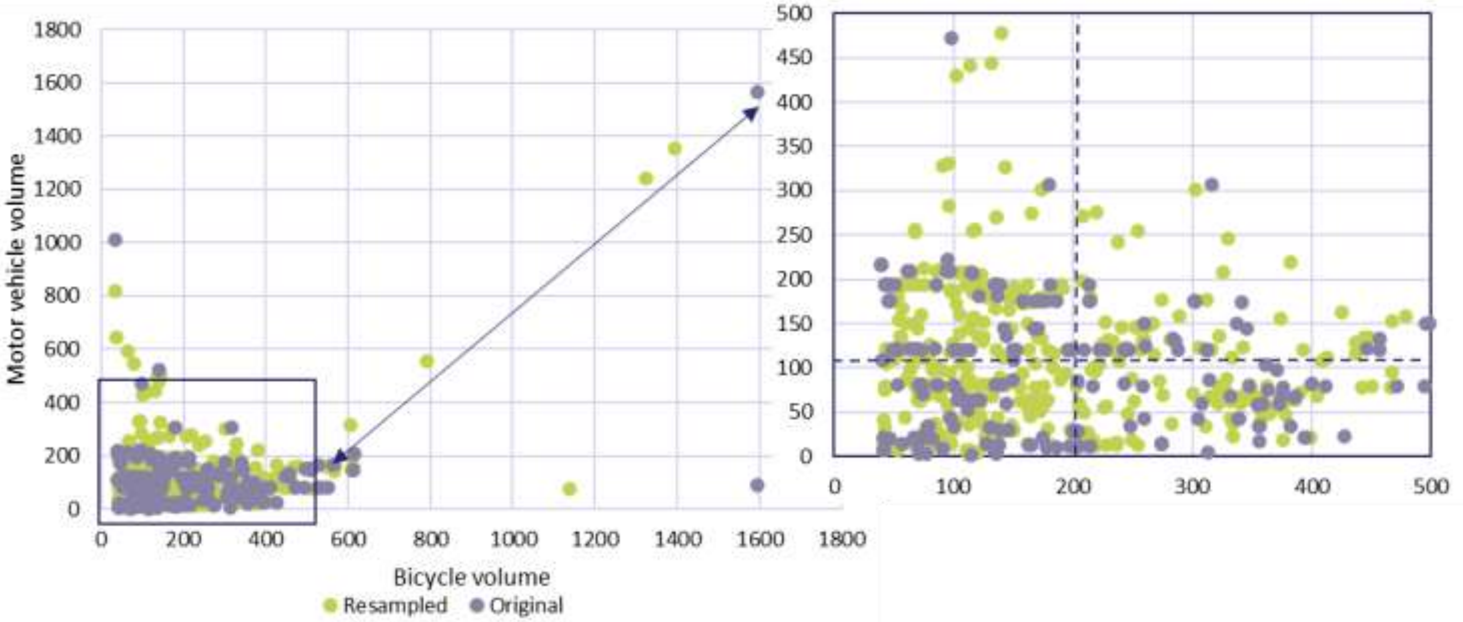

Figure 53 Example plot of original and resampled bicycle street traffic volume data, with means as dotted lines

9.3 Additional conflict study results

9.3.1 Conflict events per bicycle street

This section describes the more detailed observations of the conflict study, which cannot be generalized. On the most narrow bicycle street, the majority of conflicts resulted from oncoming encounters. In 8 out of 9 conflicts this regarded a Bicycle-MV encounter where the motor vehicle "takes" too much space by remaining on the middle of the road. This is a result of a narrow road width and parked vehicles at both sides reducing the subjectively available space. Furthermore, vehicles parked on the road or in the process of parallel parking were the direct cause of seven out of sixteen conflicts on the Cremerstraat.

On the most traditionally designed road, the Zandweg, fewest conflicts were observed but cyclist's conflict rates are high. These conflicts all consisted of a motor vehicle unsafely overtaking or staying behind the cyclist due to an oncoming cyclist. With cycling volumes of just over 200 cyclists/hour during the busiest time of day it is questionable whether this street functions as a main cycling route.

The Leidseweg is an intensively used bicycle route with one directional, low volume, motor vehicle traffic. Cyclists dominate this street with a B/MV ratio of 60(!) during rush hour. Therefore, most interactions between road users are between cyclists. When overtaking without oncoming traffic 54% of cyclists uses the opposite lane, rather than the median (32%). When there is oncoming traffic this reduces to 35%, and median use increases (48%). Two out of three cyclist-only conflicts on the Leidseweg happened when the overtaking cyclist used the opposite lane while a pair of duo-cyclists was oncoming. Next, 25% of conflicts was a result of traffic violations of motor vehicles, such as parking on the road and going against the driving direction. However, the majority of conflicts resulted from unsafe overtaking, by motor vehicles (40%) and cyclists (20%).

Despite the motor vehicle volumes on the Prins Hendriklaan being comparable to streets with bicycle lanes the conflict rates are low. Most conflicts occurred due to speeding (47%). When considering all overtaking actions, motor vehicles were speeding in 36% of actions without coming traffic and in 32% of actions with oncoming traffic. Due to the wide road lanes conflicts only occur when a motor vehicle interacts with three or four cyclists, or a cyclist and another motor vehicle.

9.3.2 Cyclist-only conflicts

The crash data analysis showed that no motorized vehicles are involved in over 25% of crashes on bicycle streets. The ratio of bicycle-bicycle crashes is higher on bicycle streets than on other bicycle facilities. However, looking at the observed safe and bothersome/dangerous interactions, bicycle-only interactions are less likely to result in conflicts (2%) than interactions with motor vehicles (9%) (Figure 54). Note that the safe interactions only include possibly critical interactions, and not simple Bicycle-overtakes-bicycle interactions. The *C+C* conflicts are mainly characterized by high numbers of cyclists, overtaking of duo- or triple-cyclists, overtaking of cyclists who are themselves overtaking, and high cycling speeds when overtaking. However, 96% of events with four or more cyclists is not bothersome or dangerous to cyclists. These results highlight the important role of motor vehicles in conflicts on bicycle streets.

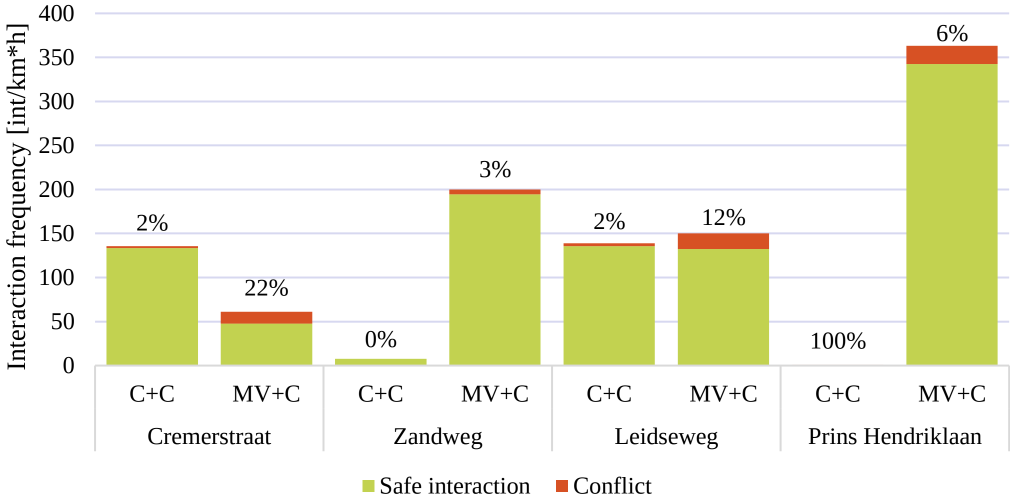

Figure 54 Bicycle-only versus motor-vehicle-involved interactions and conflicts, per km, per bicycle street

9.3.3 Rush versus non-rush hour interactions

Neither the comparison of crash cost rates, nor the regression models showed significantly large differences in the performance of bicycle streets during rush versus non-rush hours. Figure 55 distinguishes rush and non-rush interactions between road users. On the narrow type bicycle streets no conflicts were observed during non-rush hours, while, especially on the Cremerstraat, during rush hours cyclist safety was threatened by hazardous interactions. On the other hand, on the bicycle streets with medians, no significant differences were found between conflicting and safe interactions. Furthermore, this graphs shows that the number of interactions is lower during off-peak hours.

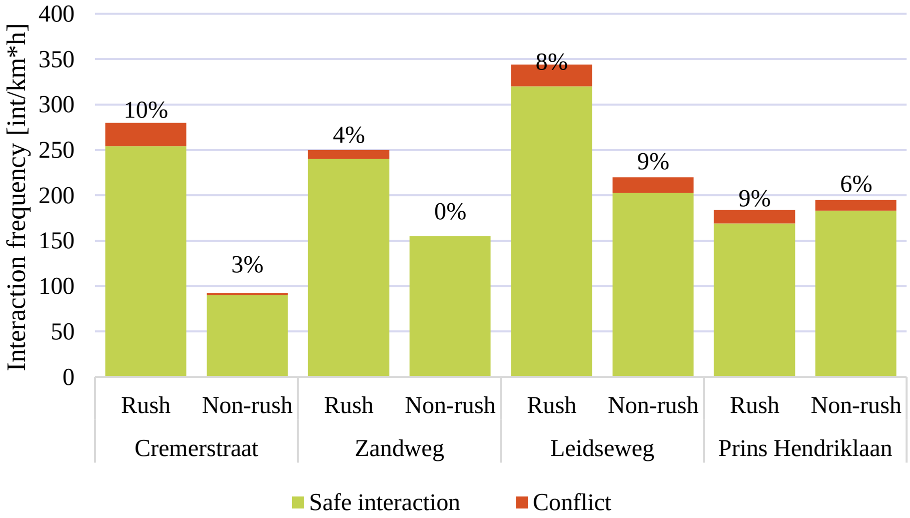

Figure 55 Rush versus non-rush interaction frequencies per bicycle street

9.3.4 The impossible, critical, and safe Interactions predictor tool

Figure 56 shows the safe, critical, and impossible vehicle combinations for different road widths used in the second step of the predictor tool, in addition to the observed safe and dangerous interactions for the four studied streets. On all streets but the *Zandweg*, critical interactions were observed while the road width should allow for safe passing. This suggests the required road with for safe interaction is more complex than summing road user widths and passing distances. Subsection 11.3.1 showed that parked vehicles reduce the effective road width, and the median limits cyclists' usable road space. Based on the conflict study findings, this study suggests a new approach to the 2nd step of the Interactions predictor tool, to better match the road width with the user interactions.

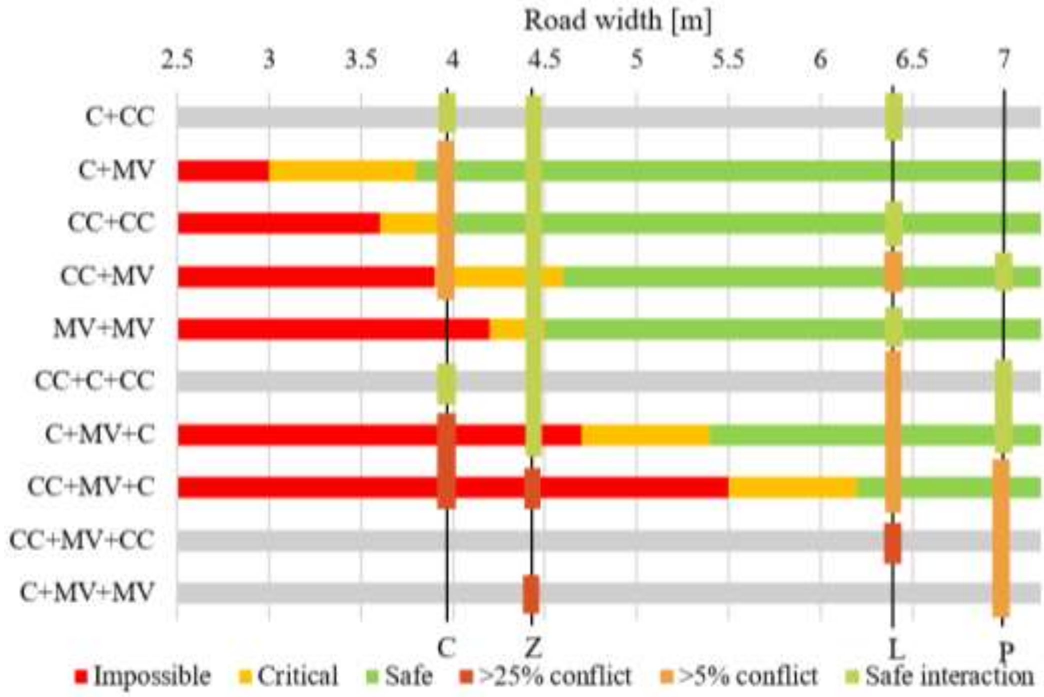

Figure 56 Observed ratio of conflicts to safe interactions between road users versus theoretically impossible, critical and spacious interactions, from Van Boggelen & Hulshof (2019)

Note: C+MV = Cyclist (C) next to (+) motor vehicle (MV), either overtaking or oncoming traffic

The main function of the rabat strip and median is to influence road user positions, placing the cyclist more in the middle of the road, and withholding motor vehicles from overtaking (Andriesse & Ligtermoet, 2005). To preserve this function, recommendations prescribe two different pavement types in one profile: red paved road lanes and tightly cobble stone paved strips and medians. This has the following effect on road positioning of cyclists, which are neglected in the Interaction predictor tool:

- The rabat strip is uncomfortable to use and often inaccessible due to parallel parked cars and the minimum distance cyclists prefer to keep to the strip's edge. A larger rabat strip therefore reduces the effective road width, until it becomes a "cycling lane".
- Cyclists keep a larger distance from vertical objects, such as parked cars, versus low objects like a sidewalk. Therefore, parallel parking facilities reduce the effective road width with 0.15m on each side.
- The presence of a median reduces the cycling positions similar to the rabat strip. Furthermore, a median of less than 0.5m is inaccessible (in a comfortable way) by cyclists.
- The road lane width of the streets with a median determines whether a cyclist can overtake a duo-cyclist without using the opposite lane. The overtaking of duo cyclists is common as they cycle slower than single cyclists. In 67% of overtaking actions of cyclists a duo cyclist group was overtook.

Based on these effects, the minimum road width for a certain road user interaction profile of n road users can be calculated follow the flowchart in figure 60. The minimum road width for narrow bicycle street (no median) depends on 1) the distance of the most right and left road users to the road edge d_{p_i-E}, 2) the width of each road user w_{p_i}, 3) and the minimum safe passing distance between the road users $d_{p_i-p_{i+1}}$ (Equation 12).

$$RW_{min} = d_{p_1-E} + \sum_{i=1}^{n} w_{p_i} + \sum_{i=1}^{n-1} d_{p_i-p_{i+1}} + d_{p_n-E} \quad (12)$$

The minimum widths of and between road users is described in van Boggelen & Hulshof (2019). The minimum distance to the road edge is the maximum of 1) the distance between the road users and a parked car or sidewalk (figure 57 left), and 2) the distance from the rabat strip, plus the rabat strip width (figure 57 right).

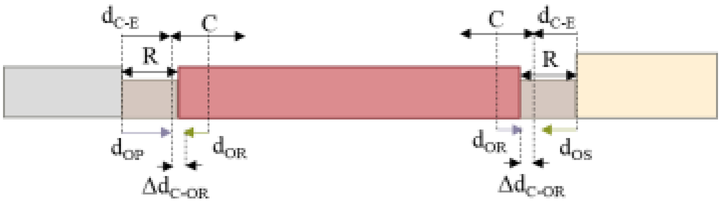

Figure 57 The minimum distance between cyclist and road edge

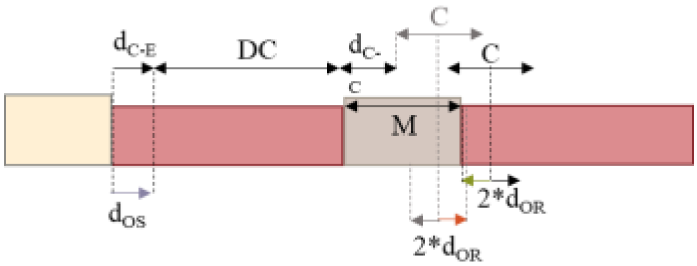

Figure 58 Example of overtaking cyclist needing to use the opposite lane

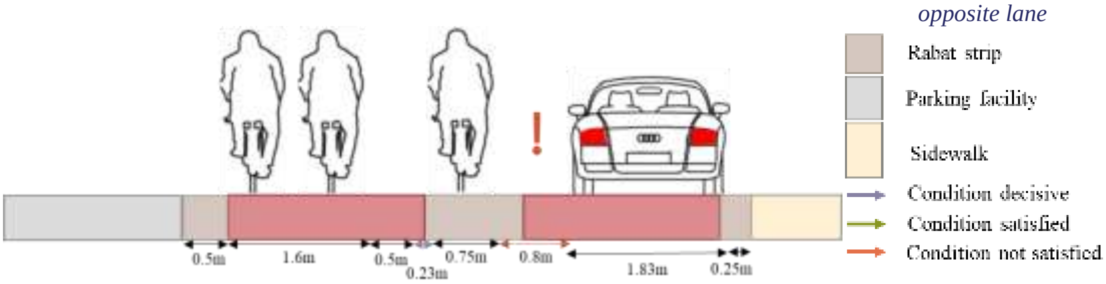

Figure 59 Example of theoretically impossible road user interaction

Figure 60 shows in a loop how the road user widths and their minimum passing distances are summed for all road users. For bicycle streets with a median, additional space between road users may be required as cyclists keep a certain distance from the edge of the median (figure 58). Here a step is added where it is checked whether the road users are "placed" upon inaccessible areas Err_x, namely the edge of the median. If so, this road user is "placed" on the next accessible location: max (Err_x).

Finally, the minimum distance between the last road user p_n and the road edge is calculated. The right column in the flowchart shows that the sum of these widths and distances results in the minimum road width to safely facilitate the interaction. Figure 59 provides an example of an unsafe road user interaction where a cyclist overtakes a group of duo-cyclists with an oncoming motor vehicle.

Table 16 Road user width and minimum passing distances

		User widths [m]		Passing distance [m]	
			C-E	d_{C-E}	Variable
Cyclist	d_C	0.75	C-C	d_{C-C}	0.50
Motor vehicle	d_{MV}	1.83	*C-MV	d_{C-MV}	0.80
Duo-bicycles	d_{DC}	1.60 (2*0.75 + 0.1)	MV-MV	d_{MV-MV}	0.30

Note: C Cyclist, E Edge, MV Motor vehicle; *at a speed of 30km/h

Table 17 Minimum and maximum distances of cyclist to obstacles

		Distance [m]
Minimum distance to obstacle rabat(/median) (measured from centre cyclist)	d_{OR}	0.25
Maximum overlap between cyclist and obstacle rabat(/median)	Δd_{C-OR}	0.125
Minimum distance to obstacle parked vehicle	d_{OP}	0.5
Minimum distance to obstacle sidewalk	d_{OS}	0.35

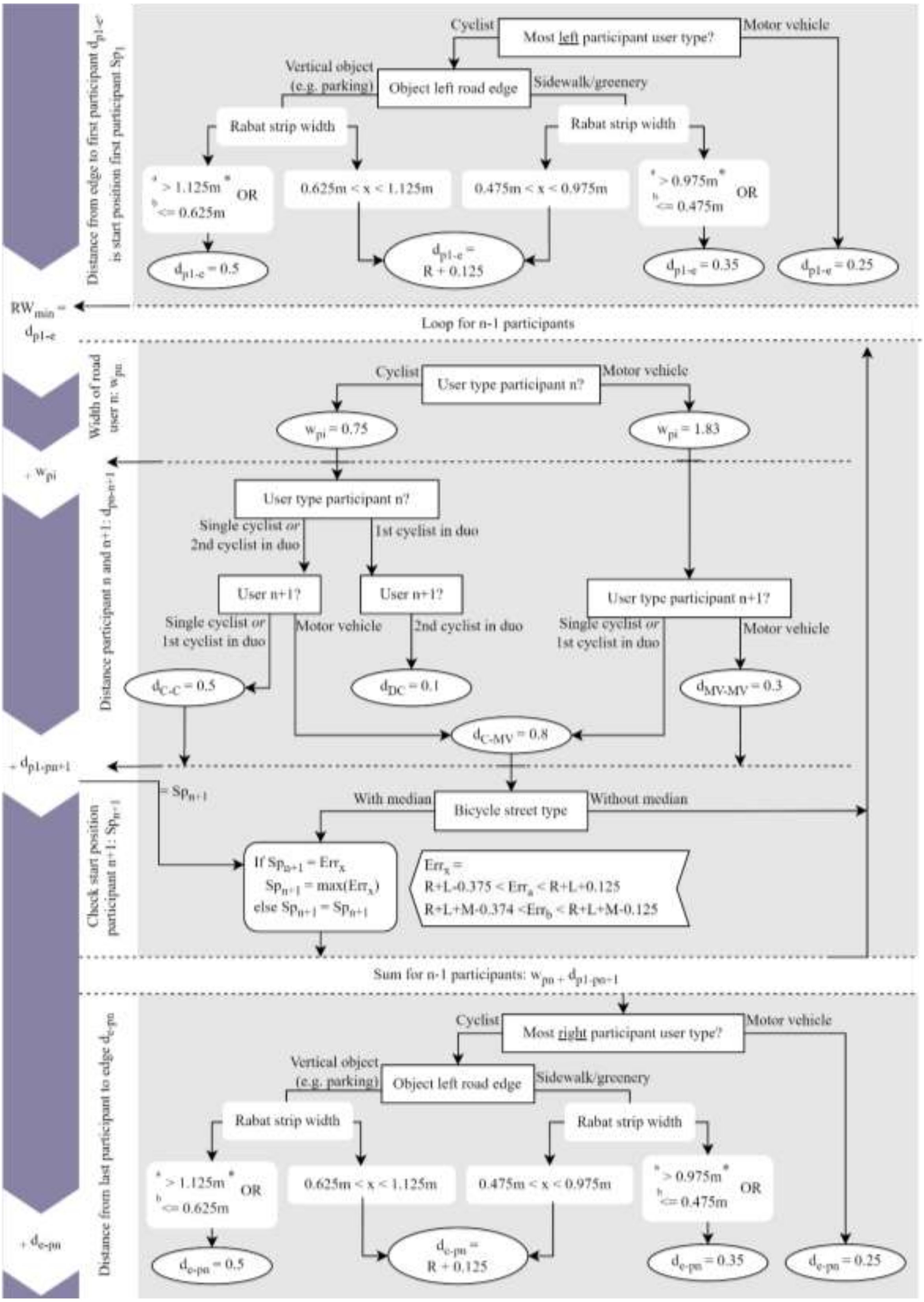

Figure 60 Flowchart for the calculation optimum bicycle street width based on a road user interaction profile

Appendix

A. Descriptive statistics of per facility (resampled and original bicycle streets)

Bicycle street (resampled)						
	Mean	Med.	Min	Max	St.D.	
Crash cost rate						
Day	77.5	0	0	4207	352	Crash cost rate per million km, for each time interval
Rush	54.2	0	0	3725	281	
Non-rush	49.4	0	0	2379	213	
Weekend	128.93	0	0	10031	831.7	
Bicycle volume						
Day	195.3	142.1	33.62	1595	167.9	
Rush	337.7	238.4	33.62	2895	307.9	Bicycle volumes [cyclists/hour]
Non-rush	164.5	111.13	33.62	1323	148.0	
Weekend	128.1	89.70	33.62	965	97.8	
Motor vehicle volume						
Day	120.9	97.7	1	1566	131.1	Motor vehicle volumes [vehicles/hour]
Rush	124.2	94.9	2	1935	162.5	
Non-rush	98.7	79.7	2	1567	128.40	
Weekend	94.2	74.0	1	1257	105.1	
Pop. Density	8863	7832	1282.9	18591	3770	Inhabitants per km2 [inh/km2]
Median Inc.	31100	27600	8400	54400	9567	Median income level in area [€]
Pop. factor						
15-25	14.72	12.282	0.742	60.55	9.891	Population factor per age group
45-65	24.29	18.59	1.043	82.52	16.29	
65+	13.46	10.43	0.453	57.03	11.77	
MXI	0.662	0.730	0.03	0.930	0.188	Mixed land use index [0-1]

Bicycle street (original)						
	Mean	Med.	Min	Max	St.D.	
Crash cost rate						
Day	79.6	0	0	4207	382	Crash cost rate per million km, for each time interval
Rush	54.9	0	0	3725	334	
Non-rush	53.0	0	0	2379	250	
Weekend	130.78	0	0	10031	896.5	
Bicycle volume						
Day	209.4	151.6	33.62	1595	190.0	
Rush	370.8	283.3	33.62	2895	350.9	Bicycle volumes [cyclists/hour]
Non-rush	174.7	112.51	33.62	1323	167.4	
Weekend	132.6	89.16	33.62	965	108.9	
Motor vehicle volume						
Day	110.9	81.5	1	1566	136.6	Motor vehicle volumes [vehicles/hour]
Rush	114.2	94.6	2	1935	167.3	
Non-rush	90.9	79.7	2	1567	133.16	
Weekend	86.9	64.8	1	1257	109.8	
Pop. Density	8453	7754	1282.9	18591	3848	Inhabitants per km2 [inh/km2]
Median Inc.	31237	27600	8400	54400	9517	Median income level in area [€]
Pop. factor						
15-25	14.41	11.522	0.742	60.55	10.768	Population factor per age group
45-65	23.32	18.59	1.043	82.52	16.96	
65+	13.14	9.33	0.453	57.03	11.88	
MXI	0.652	0.730	0.03	0.930	0.202	Mixed land use index [0-1]
Bicycle lane						

	Mean	Med.	Min	Max	St.D.	
Crash cost rate						
Day	105.3	0	0	9004	515	Crash cost rate per million km, for each time interval
Rush	123.2	0	0	30598	1072	
Non-rush	107.3	0	0	10624	597	
Weekend	85.20	0	0	30680	892.1	
Bicycle volume						
Day	259.3	156.1	37.14	2334	336.1	
Rush	379.3	204.5	37.14	4058	560.5	Bicycle volumes [cyclists/hour]
Non-rush	231.7	141.31	37.14	2234	289.1	
Weekend	205.3	129.17	37.14	1858	242.0	
Motor vehicle volume						
Day	275.3	206.8	0	2086	259.1	Motor vehicle volumes [vehicles/hour]
Rush	334.9	252.4	0	2577	320.8	
Non-rush	275.4	206.6	0	2088	258.38	
Weekend	225.6	169.5	0	1675	210.8	
Pop. Density	10146	10312	383.4	19108	4320	Inhabitants per km2 [inh/km2]
Median Inc.	30858	27800	20300	58200	8197	Median income level in area [€]
Pop. factor						
15-25	9.39	7.271	0.294	33.08	6.474	Population factor per age group
45-65	20.06	18.50	0.914	82.52	10.62	
65+	14.38	12.62	0.254	57.03	10.21	
MXI	0.716	0.760	0	0.960	0.182	Mixed land use index [0-1]

Bicycle path						
	Mean	Med.	Min	Max	St.D.	
Crash cost rate						
Day	87.8	0	0	14133	558	Crash cost rate per million km, for each time interval
Rush	102.5	0	0	37638	976	
Non-rush	91.9	0	0	26467	759	
Weekend	66.34	0	0	53641	921.9	
Bicycle volume						
Day	275.2	153.0	37.14	3143	350.3	
Rush	409.7	184.9	37.14	6268	633.7	Bicycle volumes [cyclists/hour]
Non-rush	241.1	135.84	37.14	2531	285.9	
Weekend	220.1	124.83	37.14	2192	248.1	
Motor vehicle volume						
Day	286.3	213.8	0	2452	283.6	Motor vehicle volumes [vehicles/hour]
Rush	357.3	264.1	0	3030	355.9	
Non-rush	283.9	212.6	0	2454	280.50	
Weekend	231.1	173.3	0	1969	229.7	
Pop. Density	8335	7655	201.0	19108	3794	Inhabitants per km2 [inh/km2]
Median Inc.	30915	27500	14900	58200	9271	Median income level in area [€]
Pop. factor						
15-25	11.53	9.275	0	34.04	8.179	Population factor per age group
45-65	22.43	18.84	0	82.52	14.56	
65+	15.96	10.68	0	79.68	15.92	
MXI	0.733	0.780	0	0.960	0.193	Mixed land use index [0-1]

No facility						
	Mean	Med.	Min	Max	St.D.	
Crash cost rate						
Day	66.1	0	0	20997	506	Crash cost rate per million km, for each time interval
Rush	63.5	0	0	32901	764	
Non-rush	79.4	0	0	45004	845	
Weekend	48.63	0	0	28341	655.9	
Bicycle volume						
Day	112.1	50.0	33.62	2236	146.5	
Rush	154.6	62.3	33.62	5053	256.4	Bicycle volumes [cyclists/hour]
Non-rush	101.8	46.04	33.62	1842	125.5	
Weekend	93.8	44.85	33.62	1437	106.6	
Motor vehicle volume						
Day	169.2	59.6	0	2784	261.7	Motor vehicle volumes [vehicles/hour]
Rush	216.4	77.8	0	3893	335.7	
Non-rush	166.7	59.7	0	2637	256.19	
Weekend	134.1	43.5	0	2104	212.4	
Pop. Density	7824	7174	140.9	19108	3620	Inhabitants per km2 [inh/km2]
Median Inc.	33466	29300	8400	58200	10587	Median income level in area [€]
Pop. factor						
15-25	11.22	9.169	0.181	60.55	8.751	Population factor per age group
45-65	21.82	17.37	0.914	82.52	15.51	
65+	13.76	8.03	0.254	79.68	14.37	
MXI	0.737	0.760	0	0.960	0.164	Mixed land use index [0-1]

B. Design and traffic characteristics of conflict study bicycle streets

Location		Cremerstraat	Zandweg	Leidseweg	Prins Hendriklaan
Type		I	I	II	II
Length [km]		1.25	5.29*	1.38*	0.62
Year of construction		2018	2014	2016	2013
Speed limit [km/h]		30	30	30	30
Bicycle volume*	Rush	363	156	1089	812
	Non-rush	202	113	771	499
Motor vehicle volume*	Rush	11	33	79	142
	Non-rush	6	31	53	84
Driving direction		2-sided	2-sided	1-sided (towards CC)	2-sided
Road width [m]		4.05	4.5	6.35	7
Lane width [m]		3.55	3.4	2.2	3
Lane pavement		Red asphalt	Red asphalt	Red asphalt	Red asphalt
Rabat width [m]		0.25	0.55	0.35-0.5	0
Median width [m]		NA	NA	1.1	1
Rabat/median pavement		Cobbles	Cobbles	Cobbles/& curved	Cobbles/& curved
Parking facilities		Both sides	1 side	1 side	1 side
Width parking facility [m]		1.75	2.2	2	2.3

**Design varies over the road length; **Counts from video data*

C. Two sample Z-test results (p-values) on average crash cost rates; crossing time periods and facilities

		Average	Rush	Non-rush	Weekend
Bicycle Street	Average	1	0,184	1,258	1,968
	Rush	1,816	1	2	2
	Non-rush	0,742	*1,34E-08*	1	2
	Weekend	*3,22E-02*	*1,47E-19*	*8,61E-06*	1
Bicycle Lane	Average	1	0,014	2	*5,93E-04*
	Rush	1,986	1	2	*2,36E-01*
	Non-rush	*4,34E-05*	*2,71E-30*	1	*1,73E-148*
	Weekend	1,999	1,764	2	1
Bicycle Path	Average	1	0,566	1,991	*7,84E-05*
	Rush	1,434	1	2	*1,74E-10*
	Non-rush	*0,009*	*9,15E-09*	1	*1,63E-117*
	Weekend	2	2	2	1
No Facility	Average	1	2	1,833	*6,16E-16*
	Rush	*2,74E-05*	1	*2,02E-07*	*4,60E-112*
	Non-rush	0,167	2	1	*3,84E-184*
	Weekend	2	2	2	1

		Bicycle Street	Bicycle Lane	Bicycle Path	No Facility
Average	Bicycle Street	1	1,902	0,562	1,368
	Bicycle Lane	0,098	1	*3,47E-206*	*1,29E-65*
	Bicycle Path	1,438	2	1	2
	No Facility	0,632	2	*1,23E-137*	1
Rush	Bicycle Street	1	2	1,718	2
	Bicycle Lane	*2,81E-05*	1	*1,25E-43*	1,988
	Bicycle Path	0,282	2	1	2
	No Facility	*1,46E-06*	0,012	*1,06E-178*	1
Non-rush	Bicycle Street	1	1,805	0,879	1,190
	Bicycle Lane	0,195	1	*3,92E-67*	*2,89E-39*
	Bicycle Path	1,121	2	1	2
	No Facility	0,810	2	*9,16E-15*	1
Weekend	Bicycle Street	1	0,623	0,164	*2,27E-01*
	Bicycle Lane	1,377	1	*0*	*1,82E-305*
	Bicycle Path	1,836	2	1	2
	No Facility	1,773	2	*2,87E-67*	1

Note: P < 0.01 in italic

D. Overview tables of 16 (four facilities, four time periods) Tobit regression models

	Average			Rush			Non Rush			Weekend		
						Bicycle Street						
(Intercept)	**-1381**	***	[-2091,-672]	**-3864**	***	[-5083,-2646]	**-1679**	***	[-2376,-983]	**-6415**	**	[-10906,-1924]
Bicycle volume	**0.296**	***	[0.08,0.512]	**-0.096**		[-0.509,0.317]	**0.162**	*	[-0.182,0.506]	**0.441**	-	[-0.174,1.056]
Motor vehicle volume	**-0.240**	*	[-0.438,-0.042]	**-1.101**	**	[-1.494,-0.708]	**-0.254**		[-0.589,0.081]	**-0.412**		[-0.951,0.127]
Population Density	**0.155**		[-0.106,0.416]	**1.516**	***	[1.06,1.972]	**0.672**	**	[0.269,1.075]	**0.266**		[-0.395,0.927]
Median income level	**0.812**	***	[0.494,1.13]	**2.348**	***	[1.764,2.932]	**1.414**	***	[0.878,1.95]	**0.836**	**	[-0.006,1.678]
MXI	**-0.100**		[-0.318,0.118]	**-0.474**	**	[-0.853,-0.095]	**-0.379**		[-0.704,-0.054]	**0.117**		[-0.503,0.737]
PF 15-25	**0.275**	-	[-0.031,0.581]	**-1.169**	*	[-2.175,-0.163]	**0.983**	***	[0.503,1.463]	**-1.296**	-	[-2.735,0.143]
PF 45-65	**-0.352**	*	[-0.677,-0.027]	**-0.247**		[-0.913,0.419]	**-0.564**	*	[-1.077,-0.051]	**0.303**		[-0.696,1.302]
PF 65+	**0.080**		[-0.175,0.335]	**0.664**	**	[0.244,1.084]	**0.078**		[-0.395,0.551]	**0.330**		[-0.307,0.967]
						Bicycle Lane						
(Intercept)	**-895.4**	***	[-1230,-561]	**-4118**	***	[-5346,-2890]	**-1761**	***	[-2335,-1186]	**-5166**	***	[-6594,-3739]
Bicycle volume	**0.147**	*	[0.028,0.266]	**0.270**	-	[-0.005,0.545]	**0.196**	**	[0.05,0.342]	**0.403**	**	[0.173,0.633]
Motor vehicle volume	**0.024**		[-0.046,0.094]	**0.030**		[-0.06,0.12]	**0.045**		[-0.071,0.161]	**0.133**		[-0.045,0.311]
Population Density	**0.243**	***	[0.144,0.342]	**0.439**	***	[0.257,0.621]	**0.347**	***	[0.205,0.489]	**0.605**	***	[0.358,0.852]
Median income level	**0.048**		[-0.046,0.142]	**0.054**		[-0.126,0.234]	**0.000**		[-0.162,0.162]	**-0.037**		[-0.289,0.215]
MXI	**-0.022**		[-0.116,0.072]	**-0.132**		[-0.294,0.03]	**0.057**		[-0.082,0.196]	**-0.087**		[-0.312,0.138]
PF 15-25	**-0.051**		[-0.165,0.063]	**0.108**		[-0.087,0.303]	**-0.046**		[-0.211,0.119]	**-0.395**	**	[-0.693,-0.097]
PF 45-65	**0.047**		[-0.082,0.176]	**-0.078**		[-0.305,0.149]	**-0.035**		[-0.227,0.157]	**0.397**	*	[0.085,0.709]
PF 65+	**-0.140**	*	[-0.261,-0.019]	**-0.013**		[-0.228,0.202]	**-0.219**	*	[-0.4,-0.038]	**-0.061**		[-0.348,0.226]

*Note: With the standardized coefficient in bold; the p-value as ***p < 0.001; **p < 0.01; *p>0,05; -p < 0.1; the confidence interval at 95% in brackets.*

	Average			Rush			Non Rush			Weekend		
Bicycle Path												
(Intercept)	**-1784**	***	[-2003,-1564]	**-5682**	***	[-6350,-5014]	**-3945**	***	[-4409,-3480]	**-8553**	***	[-9633,-7473]
Bicycle volume	**0.196**	***	[0.157,0.235]	**0.367**	***	[0.287,0.447]	**0.227**	***	[0.177,0.277]	**0.469**	***	[0.311,0.627]
Motor vehicle volume	**-0.049**	***	[-0.075,-0.023]	**0.007**		[-0.018,0.032]	**-0.069**	**	[-0.118,-0.02]	**-0.139**	-	[-0.283,0.005]
Population Density	**0.241**	***	[0.204,0.278]	**0.251**	***	[0.201,0.301]	**0.389**	***	[0.338,0.44]	**0.728**	***	[0.57,0.886]
Median income level	**0.010**		[-0.028,0.048]	**0.028**		[-0.027,0.083]	**0.007**		[-0.052,0.066]	**-0.031**		[-0.234,0.172]
MXI	**0.022**		[-0.012,0.056]	**0.005**		[-0.044,0.054]	**0.021**		[-0.033,0.075]	**0.218**	*	[0.048,0.388]
PF 15-25	**0.009**		[-0.032,0.05]	**-0.006**		[-0.066,0.054]	**0.006**		[-0.059,0.071]	**0.231**	*	[0.039,0.423]
PF 45-65	**-0.055**	*	[-0.1,-0.01]	**0.001**		[-0.064,0.066]	**-0.130**	***	[-0.203,-0.057]	**-0.240**	*	[-0.461,-0.019]
PF 65+	**-0.030**	-	[-0.065,0.005]	**-0.061**	*	[-0.112,-0.01]	**0.019**		[-0.037,0.075]	**-0.168**	-	[-0.347,0.011]
No Facility												
(Intercept)	**-1477**	***	[-1838,-1117]	**-4251**	***	[-5322,-3181]	**-5301**	***	[-6306,-4295]	**-5941**	***	[-7519,-4363]
Bicycle volume	**0.086**	***	[0.065,0.107]	**0.370**	***	[0.256,0.484]	**0.084**	***	[0.059,0.109]	**0.322**	***	[0.199,0.445]
Motor vehicle volume	**0.009**		[-0.028,0.046]	**0.081**		[-0.034,0.196]	**0.018**		[-0.038,0.074]	**0.132**		[-0.1,0.364]
Population Density	**0.158**	***	[0.111,0.205]	**0.440**	***	[0.222,0.658]	**0.216**	***	[0.154,0.278]	**0.692**	***	[0.399,0.985]
Median income level	**-0.055**	-	[-0.109,-0.001]	**-0.483**	**	[-0.761,-0.205]	**0.018**		[-0.061,0.097]	**-0.532**	**	[-0.897,-0.167]
MXI	**-0.083**	***	[-0.123,-0.043]	**-0.286**	**	[-0.466,-0.106]	**-0.092**	**	[-0.145,-0.039]	**-0.464**	***	[-0.701,-0.227]
PF 15-25	**-0.014**		[-0.06,0.032]	**-0.099**		[-0.301,0.103]	**-0.002**		[-0.063,0.059]	**-0.505**	**	[-0.835,-0.175]
PF 45-65	**-0.085**	*	[-0.154,-0.016]	**-0.137**		[-0.459,0.185]	**-0.131**	**	[-0.225,-0.037]	**0.150**		[-0.311,0.611]
PF 65+	**-0.031**		[-0.091,0.029]	**-0.222**		[-0.51,0.066]	**-0.019**		[-0.102,0.064]	**-0.322**		[-0.727,0.083]

E. Noted bicycle streets in Fietsersbond (2020) network and corrections

Mun.	*Bicycle streets (Fietsersbond)*	*Facility following criteria*
Utrecht	Kanaalweg	Bicycle street
	Opaalweg	Bicycle street
	Cremerstraat	Bicycle street
	Texel	Bicycle street
	Houtensepad	Bicycle street
	Kapteynlaan	Bicycle lane
	Havenweg	Bicycle street
	Engelsmanplaat	Bicycle street
	Impalastraat	No facility
	Zandweg	Bicycle street
	Keulsekade	Bicycle street
	Nieuwe Houtenseweg	Bicycle street
	Troelstralaan	Bicycle street
	Everard Meijsterlaan	Bicycle street
	Leidseweg	Bicycle street
	Sluizencomplex	No facility
	Prins Hendriklaan	Bicycle street
	Platolaan	Bicycle street
	Stadsdambrug	No facility
	Aartsbiss Romerostraat	Bicycle lane
	Julianaweg	No facility
	Kariboestraat	Bicycle street
	2e Polderweg	Bicycle path
	Sophocleslaan	Bicycle street
	Lamstraat	Bicycle street
	Laan van Puntenburg	Bicycle path
	Verlengde Hoogravenseweg	No facility
	Rijksstraatweg	Bicycle street
	Stationsplein	Other
	Kloosterpark	Bicycle path
	Oswald Wenckebachhof	No facility
	Charlotte van Pallandhof	No facility
	Beeldhouwersdijk	Bicycle path
	Oude Liesbosweg	Bicycle street
	Eschersingel	No facility
Rotterdam	Maastunnelplein NO	Bicycle street
	Maastunnelplein ZW	Bicycle street
	Brielselaan	Bicycle street
	Teilingerstraat	Bicycle street
	Gladiolusstraat	Bicycle street
	Molenvliet	Bicycle street
	Stadionlaan	Bicycle street
Amsterdam	Frederiksplein	Added as Bicycle street
	J. van Wassenaar Obdamstraat	No facility
	Chasséstraat	Bicycle street
	Weteringschans	Bicycle street
	Sarphatistraat	Bicycle street
	Zaanstraat	Bicycle street
	Kortenaerstraat	No facility
	Vikingpad	Bicycle street
	Buikslotermeerdijk	Bicycle lane
	Jachthavenweg	Bicycle street
	Ringvaartdijk	No facility
	Erasmusgracht	Bicycle street
	Beemsterstraat	Bicycle lane

The Hague	Conradkade	Bicycle street
	Suezkade	No facility
	Laakweg	Bicycle street
	Laurens Reaelstraat	No facility
	Trekweg	Bicycle street
	Cromvlietkade	Bicycle street
	Veenweg	Bicycle street
	Strijpkade	Bicycle street
	Schrepelpad	Bicycle street
	Voetgangersdoorsteekje	No facility
	Laakkade	No facility
	Monsterseweg	Bicycle path
	Stenen Kamer	No facility
	Nieuwe Parklaan	Bicycle street

F. Design descriptives of the bicycle streets included in the crash cost rate analysis

Mun.	Bicycle street name	Constr. year	Length [m]	Road width	Road lane width	Roadway pavement	Rabat strip width	Rabat strip pavement	Central reserve	Central line	Road side parking
Utrecht	Kanaalweg	2014	487.5	5.4	4.0	asphalt	0.69	cobbles	0	0	1
	Opaalweg	2012	226.2	5.1	4.0	asphalt	0.54	cobbles	0	0	1
	Cremerstraat	2018	1249.3	4.0	3.6	asphalt	0.24	cobbles	0	0	1
	Texel	2015	130.0	4.5	3.6	asphalt	0.45	cobbles	0	0	1
	Houtensepad	2015	680.5	5.1	4.0	asphalt	0.54	cobbles	0	0	1
	Havenweg	2015	390.0	5.1	4.0	asphalt	0.57	cobbles	0	0	1
	Engelsmanplaat	2013	16.8	4.5	3.6	asphalt	0.45	cobbles	0	0	1
	Zandweg	2014	5285.9	4.4	3.3	asphalt	0.55	cobbles	0	0	0
	Keulsekade	2015	1814.5	5.1	4.0	asphalt	0.57	cobbles	0	0	1
	Nieuwe Houtenseweg	2014	1202.0	5.5	3.9	asphalt	0.79	cobbles	0	0	1
	Troelstralaan	2013	555.4	4.6	3.6	asphalt	0.5	cobbles	0	0	1
	Everard Meijsterlaan	2015	525.8	3.9	3.9	asphalt	0	na	0	0	1
	Leidseweg	2016	1380.3	5.4-6.5	4.3-5.4	asphalt	0.54	cobbles	1	0	1
	Prins Hendriklaan	2013	629.8	7.4	7.4	asphalt	0	na	1	0	1
	Platolaan	2014	269.0	7.4	7.4	asphalt	0	na	1	0	1
	Kariboestraat	2014	206.3	5.1	4.0	asphalt	0.54	cobbles	0	0	1
	Sophocleslaan	2013	112.0	7.4	7.4	asphalt	0	na	1	0	1
	Lamstraat	2014	65.0	5.1	4.0	asphalt	0.54	cobbles	0	0	1
	Rijksstraatweg	2014	103.9	4.6	3.6	asphalt	0.5	cobbles	0	0	0
	Oude Liesbosweg	2016	209.6	5.1	4.0	asphalt	0.54	cobbles	0	0	1
Rotterdam	Maastunnelplein NO	2009	55.8	4.8	3.7	asphalt	0.55	cobbles	0	1	1
	Maastunnelplein ZW	2009	53.2	3.6	2.2	asphalt	0.66	cobbles	0	0	1
	Brielselaan	2010	551.9	4.1	3.2	asphalt	0.45	cobbles	0	0	1
	Teilingerstraat	2009	418.9	6.6	4.9	asphalt	0.84	cobbles	1	0	1
	Gladiolusstraat	2017	170.9	4.5	3.5	asphalt	0.5	cobbles	0	0	1
	Molenvliet	2015	194.4	3.5	2.0	asphalt	0.74	cobbles	0	0	1
	Stadionlaan	2016	453.7	6.0	5.0	asphalt	0.5	cobbles	1	0	1
Amsterdam	Frederiksplein	2015	629.97	4.8	4.0	asphalt	0.4	asphalt	0	0	1
	Chasséstraat	2016	150.7	3.7	2.7	cobbles	0.5	cobbles	0	0	1
	Weteringschans	2015	1270.4	4.8	4.0	asphalt	0.4	asphalt	0	0	1
	Sarphatistraat	2015	2052.2	4.8	4.0	asphalt	0.4	asphalt	0	0	1
	Zaanstraat	2011	928.6	4.8	2.8	asphalt	1	cobbles	0	0	1
	Vikingpad	2016	438.8	5.2	3.2	asphalt	1	asphalt	0	0	0
	Jachthavenweg	2013	196.3	3.8	3.2	asphalt	0.3	asphalt	0	1	0
	Erasmusgracht	2012	58.6	4.6	3.6	asphalt	0.5	cobbles	0	0	1
The Hague	Conradkade	2018	1033.4	4.1	3.0	asphalt	0.54	cobbles	0	1	1
	Laakweg	2009	491.5	4.0	2.9	asphalt	0.55	cobbles	0	1	1
	Trekweg	2012	740.4	4.0	3.0	asphalt	0.5	cobbles	0	0	1
	Cromvlietkade	2012	525.3	4.0	3.0	asphalt	0.5	cobbles	0	0	1
	Veenweg	2013	1404.9	4.2	3.4	asphalt	0.4	cobbles	0	1	0
	Strijpkade	2011	802.7	3.0	3.0	asphalt	0	na	0	0	0
	Schrepelpad	2018	128.3	5.2	3.6	asphalt	0.8	asphalt	0	1	0
	Nieuwe Parklaan	2016	302.0	4.1	3.0	asphalt	0.55	cobbles	0	1	1