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To cite this article: Teun Uijtdewilligen, Mehmet Baran Ulak, Gert Jan Wijlhuizen, Frits Bijleveld, Karst T. Geurs & Atze Dijkstra (06 Nov 2023): Examining the crash risk factors associated with cycling by considering spatial and temporal disaggregation of exposure: Findings from four Dutch cities, Journal of Transportation Safety & Security, DOI: [10.1080/19439962.2023.2273547](https://doi.org/10.1080/19439962.2023.2273547)

To link to this article: <https://doi.org/10.1080/19439962.2023.2273547>



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Published online: 06 Nov 2023.



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# Examining the crash risk factors associated with cycling by considering spatial and temporal disaggregation of exposure: Findings from four Dutch cities

Teun Uijtdewilligen<sup>a,b</sup> , Mehmet Baran Ulak<sup>a</sup> , Gert Jan Wijnhuizen<sup>b</sup>,  
Frits Bijleveld<sup>b</sup> , Karst T. Geurs<sup>a</sup> , and Atze Dijkstra<sup>b</sup>

<sup>a</sup>Faculty of Engineering, Transport Engineering and Management, University of Twente, Enschede, The Netherlands; <sup>b</sup>SWOV Institute for Road Safety Research, The Hague, The Netherlands

## ABSTRACT


Cycling levels in cities keep increasing, which is accompanied with more cyclists being involved in serious road crashes. This paper aims to contribute to safer urban cycling by examining risk factors associated with cycling in the four largest Dutch cities, incorporating spatial and temporal variations in bicycle crash risk. For this purpose, the crashes and exposure metrics are analysed on an hourly temporal resolution. The results reveal that utilising an hourly temporal resolution in the exposure metrics and bicycle crash risk gives more detailed results compared to daily averages of these metrics. Moreover, the exposure to cyclists and motorised vehicles both have a significant impact on bicycle crash risk. The results also imply that separating cyclists from high-speed motorised vehicles might be more important than implementing a lower speed limit to curb the increasing severity of crashes. Despite some local differences, the overall results of the risk factors are remarkably similar across the cities, providing increased generalisability and transferability of the study. The findings indicate that concerns about the effects of increasing bicycle use and large flows of motorised vehicles on bicycle crash risk are valid, showing the importance of efforts towards improving bicycle safety in cities.

## KEYWORDS

bicycle safety; temporally refined exposure; betweenness centrality; cycling infrastructure effects

## 1. Introduction

Cycling gains popularity in many cities around the globe due to investments in cycling infrastructure and promotion of cycling as a green and healthy mode of transport. Although the majority of the European cities had

**CONTACT** Teun Uijtdewilligen  [t.ujtdewilligen@utwente.nl](mailto:t.ujtdewilligen@utwente.nl)  Faculty of Engineering, Transport Engineering and Management, University of Twente, PO Box 217, 7500 AE Enschede, The Netherlands.

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relatively constant cycling levels between 1990 and 2017, the measures taken by local authorities to counter the COVID-19 pandemic from 2019 to 2020 acted as a catalyst to increase cycling (Buehler & Pucher, 2021; Schepers et al., 2021). Consequently, the growing cycling levels lead to an increasing number of severe and fatal bicycle crashes, particularly in urban areas where more than half (56%) of the fatal bicycle crashes in the European Union occurred (Adminaité-Fodor & Jost, 2020; European Commission, 2022). Therefore, understanding the factors affecting bicycle safety in urban areas is still crucial to improve the well-being of cyclists and further promote cycling as a sustainable and healthy mode of transport. This paper aims to contribute to safer urban cycling by examining bicycle crash risk factors in Dutch cities.

Road safety literature shows that bicycle crashes have a strong spatiotemporal character (Loidl et al., 2016; Lovelace et al., 2016; Ulak et al., 2018), and studies taking temporal variation into account found that the number of bicycle crashes is higher during peak hours and on specific days of the week (Dozza, 2017; Ferster et al., 2021; Lücken & Wagner, 2020). Previously, Uijtdewilligen et al. (2022) showed that hourly variation in the exposure to cyclists and motorised vehicles have a substantial effect on the bicycle crash frequency. These studies verify that the relationship between bicycle crashes and traffic exposure can be explained better by considering the temporal aspects. In addition, bicycle crashes are found unevenly distributed not only temporally over the hours of the week but also spatially over the cycling network (Loidl et al., 2016; Mukoko & Pulugurtha, 2020). Studies involving both the spatial and temporal character of bicycle crashes show that bicycle crashes tend to cluster at specific locations and that this spatial heterogeneity is influenced by temporal variation in crashes (Loidl et al., 2016; Ulak et al., 2018; Wang, Chang et al., 2019). This nature of bicycle crashes compels an investigation of bicycle safety by considering the heterogeneity of crashes over space and time.

Several shortcomings exist in this literature about bicycle safety. First, in most of the abovementioned studies, either the exposure to cyclists or motorised vehicles, or both in some cases, are absent and the level of temporal resolution is rather limited. Second, several studies are city-specific (Aldred et al., 2018; Dozza, 2017; Ferster et al., 2021), which makes identified risk factors associated with cycling less transferable to other locations and potentially difficult to generalise. Third, another gap in the literature is contradictory findings about the safety of bicycle lanes (DiGioia et al., 2017; Mulvaney et al., 2015). Last, in the Dutch context, the number of studies examining the safety of different types of cycling infrastructure is limited. One important study in this field is rather old and the findings may be difficult to apply on current urban cycling (Welleman & Dijkstra, 1988). A more recent study shows important findings on this topic, but the

results are city-specific and limited to only roads with 50 km/h speed limit (van Petegem et al., 2021).

To address the limitations in the literature, this paper examines bicycle crash risk using a high-resolution spatiotemporal dataset. For this purpose, bicycle crashes and exposure metrics are spatially and temporally disaggregated to determine hourly variation in these metrics on each road section of the cycling network. Furthermore, static risk factors such as network structure, cycling infrastructure type, speed limits, and popular destinations for cyclists are also analysed. To provide the transferability of the results, the cycling networks of the four largest Dutch cities are analysed simultaneously. The novelty of the approach in this study is threefold: (1) the cycling-related risk factors are examined across several cycling-friendly cities, (2) a highly detailed spatiotemporal approach is adopted, which includes both the exposure to cyclists and motorised vehicles, and (3) it provides evidence that an hourly approach leads to more detailed results than daily averages.

## **2. Literature review**

### ***2.1. Temporal variation in the relationship between exposure and bicycle safety***

The majority of the studies that investigate the relationship between exposure and bicycle safety use daily averages of traffic volumes as the main predictor. However, daily averages may not be detailed enough to unravel the effect of exposure on bicycle safety. Studies adopting a finer temporal resolution commonly found that during the peak hours, when exposure levels are highest, the number of bicycle crashes is higher compared to other times of the day (Ferster et al., 2021; Uijtdewilligen et al., 2022; Wang, Chang et al., 2019). Other findings show that during the weekend nights, more crashes occur than expected given the levels of exposure (Dozza, 2017). In addition, Lücken and Wagner (2020) used various temporal scales and found that on an annual scale, crash risk for cyclists decreases with an increase in bicycle volume, while on a monthly and daily scale they found an increased crash risk with higher bicycle volumes. A typical drawback in these studies is the exclusion of the exposure to motorised vehicles, which is one of the most important predictors of bicycle crashes. Other drawbacks are the lack of road geometry data in the analysis and the low level of temporal resolution. To address these limitations for a better investigation of bicycle safety, a finer temporal resolution of both the exposure to cyclists and motorised vehicles as well as including road geometry data is necessary.

## **2.2. Relationships between network structure and bicycle safety**

This study examines three important network-related characteristics that impact bicycle safety: centrality, intersection density, and grade-separated road sections (e.g. bridges, tunnels, and viaducts). Centrality determines the importance of a road section in a network, which means that central road sections are more accessible from other parts of the network and therefore attract more road users (Kamel & Sayed, 2021; Porta et al., 2009). Moreover, intersections are locations in the network where several traffic flows meet and intersection density measures how close to each other intersections are in a network (Kamel & Sayed, 2021). For example, a higher intersection density indicates that more flows of traffic meet closer to each other, which leads to an increased number of bicycle crashes (Nashad et al., 2016; Osama & Sayed, 2016; Wei & Lovegrove, 2013). Similarly, grade-separated road sections are bottlenecks of the network as they force flows of traffic to one location. These increased traffic volumes at grade-separated road sections are distributed over less space. Since these road sections are also characterised by abrupt changes in the infrastructure, increased numbers of conflicts tend to occur (Vandenbulcke et al., 2014; Wang, De Backer et al., 2019). In other words, these network-related characteristics all attract or force different traffic flows to meet at one point in the network, which has consequences for bicycle safety (Elvik, 2006; Kamel & Sayed, 2021; Kaplan & Prato, 2015; Wang, De Backer et al., 2019). Note that a common limitation of these studies is that the findings are case study-specific, which prevents better generalisation of the results. The present study therefore includes the cycling networks of the four largest Dutch cities.

## **2.3. Cycling infrastructure and safety**

Cycling infrastructure is highly associated with bicycle safety (Salmon et al., 2022). Three types of cycling infrastructure are prevalent in the Netherlands: separated bicycle tracks, bicycle lanes (marked on the carriageway), and mixed traffic conditions (cyclists sharing the road with motorised vehicles). Several studies showed that separated bicycle tracks are the safest for cyclists (van Petegem et al., 2021; Wang, Chang et al., 2019), as the majority of interactions are between cyclists and the interactions with motorised vehicles only take place at intersections or at locations where cyclists cross the road (Twisk et al., 2013; Vandenbulcke et al., 2014). Consequently, after correcting for bicycle volumes, the risk per cyclist is lower compared to other cycling infrastructure types (Thomas & De Robertis, 2013).

Despite the findings on separated bicycle tracks, literature is inconsistent regarding the safety of bicycle lanes. Some studies identified an improvement in bicycle safety on roads with bicycle lanes (DiGioia et al., 2017; Mulvaney et al., 2015; Pulugurtha & Thakur, 2015), while other studies found no added safety benefits compared to mixed traffic conditions (Mulvaney et al., 2015; van Petegem et al., 2021), or even a deterioration in safety (DiGioia et al., 2017; Mulvaney et al., 2015). Moreover, Welleman and Dijkstra (1988) compared separated bicycle tracks with bicycle lanes and roads with mixed traffic conditions. They found that, after correcting for exposure, bicycle lanes are more risky compared to bicycle tracks and mixed traffic conditions.

#### **2.4. The effect of destinations on bicycle safety**

Four types of popular destinations for cyclists can be distinguished in travel behaviour literature: commercial facilities (e.g. shops, restaurants, bars), offices, railway stations, and educational facilities (Bernardi et al., 2018; Cui et al., 2014; Faghih-Imani et al., 2014; Givoni & Rietveld, 2007; Gleave, 2012; Harms et al., 2014). Commercial areas are identified as risk increasing locations for cyclists and the crashes occur mostly in the weekend and during off-peak hours (Ferster et al., 2021; Merlin et al., 2020; Mukoko & Pulugurtha, 2020). Moreover, office areas also pose a higher bicycle crash risk due to the large amount of business activity leading to more complex situations, especially during peak hours (Ferster et al., 2021; Williams et al., 2018). Schepers (2021) showed that in Dutch urban areas traffic safety slightly deteriorates close to railway stations and schools. The latter is also confirmed by several other studies (Loidl et al., 2016; Merlin et al., 2020; Mukoko & Pulugurtha, 2020).

### **3. Data**

#### **3.1. Study area**

The study area covers the four largest Dutch cities: Amsterdam (883,000 inhabitants), Utrecht (362,000 inhabitants), Rotterdam (655,000 inhabitants), and The Hague (553,000 inhabitants) (Statistics Netherlands [CBS], 2022). Table 1 shows that Amsterdam has the largest share of roads with a separated bicycle track (30%) and Utrecht has most bicycle priority streets<sup>1</sup> (2%). Rotterdam and The Hague, on the other hand, have the largest share of roads with a bicycle lane (5%) (Dutch Cyclists' Union, 2020). Figure 1 shows examples of cycling infrastructure types mentioned in Table 1. Despite the rather small differences, the infrastructure of Rotterdam and The Hague is characterised by large, multiple-lane, distributor roads which are designed for large flows of motorised vehicles. Furthermore, in 2015, nearly 40% of the short



**Table 1.** The total length and share per city of different types of cycling infrastructure used in this study.

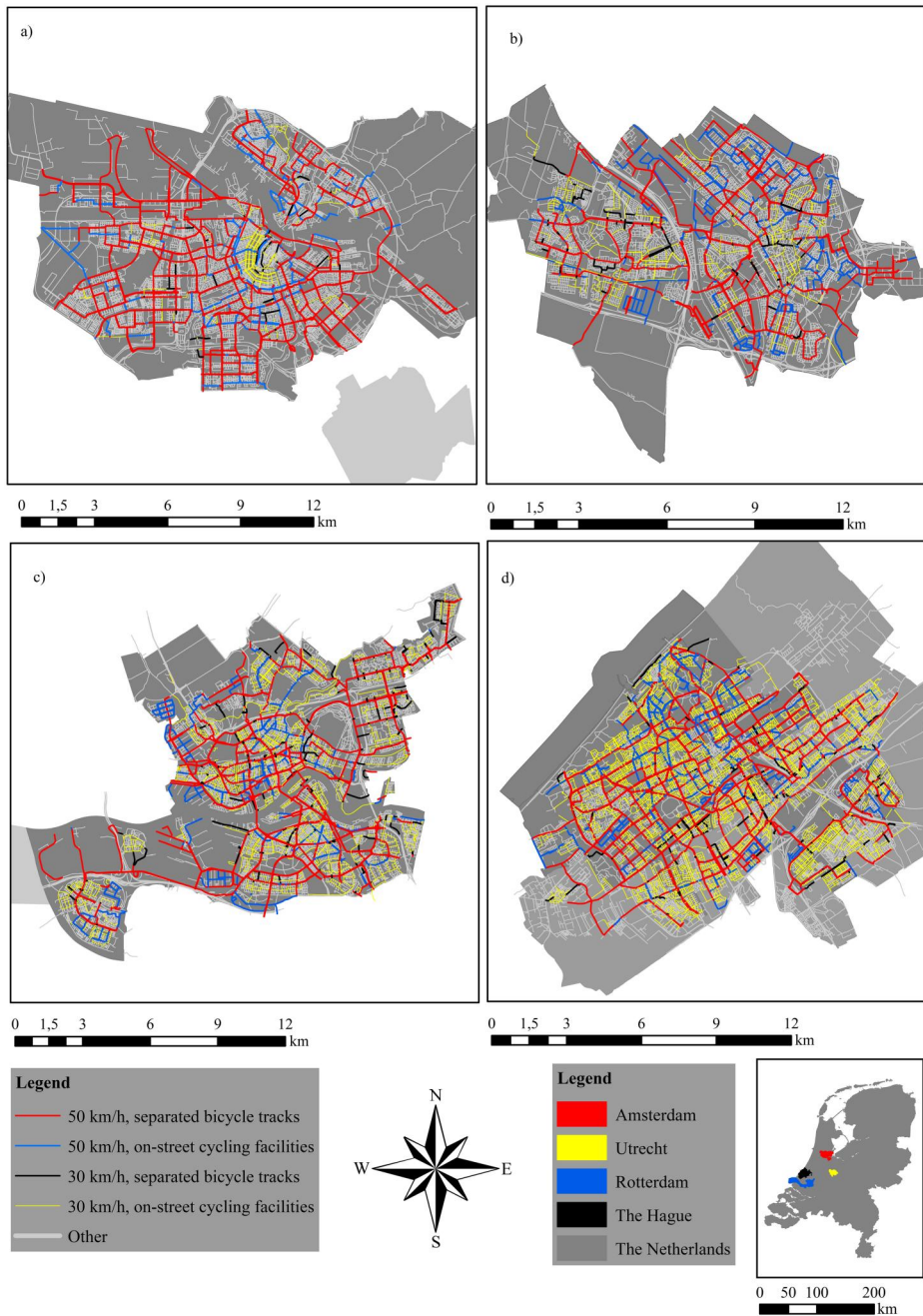
	Amsterdam		Utrecht		Rotterdam		The Hague	
	km	%	km	%	km	%	km	%
<i>Separated bicycle tracks</i>								
Separated bicycle tracks	577	33.9	263	24.8	489	30.3	341	27.6
<i>On-street cycling facilities</i>								
Bicycle lanes	67	3.9	42	4.0	84	5.2	67	5.4
Bicycle priority streets	5	0.3	21	2.0	2	0.1	6	0.5
Mixed traffic conditions	1,054	61.9	733	69.2	1,039	64.4	823	66.5
<i>Total</i>	<i>1,703</i>	<i>100.0</i>	<i>1,059</i>	<i>100.0</i>	<i>1,614</i>	<i>100.0</i>	<i>1,237</i>	<i>100.0</i>

**Figure 1.** Example figures of cycling infrastructure types present in the study area: (a) separated bicycle tracks, (b) bicycle lanes, (c) bicycle priority streets, and (d) mixed traffic conditions (© Paul Voorham).

trips (1-7 km) were made by bicycle in Amsterdam and Utrecht; for cars this was around 25%. For Rotterdam and The Hague, around 30% of these trips were made by bicycle and 30% by car (Jonkeren et al., 2019). This illustrates the difference in cycling levels between cities with more cycling-friendly and more car-oriented infrastructure. Figure 2 shows the road networks of the four cities, where the highlighted roads are analysed.

### 3.2. Crash data

The most comprehensive bicycle crash data that include crash location and currently available for research are obtained from the Database of



**Figure 2.** The analysed cycling network of (a) Amsterdam, (b) Utrecht, (c) Rotterdam, and (d) The Hague.

Registered Crashes in the Netherlands (BRON) (Rijkswaterstaat, 2020a). This dataset consists of police-reported crashes. All reported injury (light or severe) and fatal crashes involving at least one cyclist and that occurred



on road sections or intersections in the analysed networks between 2015 and 2019 are included in this study. The majority of analysed crashes are injury crashes (4,615 in total for all cities) while only a few are fatal crashes (50 in total for all cities). Most of the crashes are bicycle-to-motorised vehicle crashes.

### 3.3. Data for predictors

A consequence of analysing four cities in one study is that there are large differences between the data sources and the datasets, which is illustrated by Table 2. Four types of data are used to estimate network-wide hourly exposure. Uijtdewilligen et al. (2022) indicated that the GPS tracks from the Dutch Bicycle Counting Week, together with local hourly bicycle count data from count stations, are useful predictors of network-wide hourly bicycle volumes. Hourly motorised vehicle count data and estimations of the weekly average volumes from local transport models are used to retrieve network-wide hourly motorised vehicle volumes.

Since the majority of urban roads in the Netherlands have a 30 km/h or 50 km/h speed limit and most cyclists in urban areas use these roads, only the roadways with a 30 km/h or 50 km/h speed limit are used in this study. These speed limits are also used to select the corresponding road sections from the base network and the transport models. The transport models of Amsterdam and Utrecht include most of the 50 km/h roads and a small

**Table 2.** List of data and sources.

Data	Source
<i>Exposure data</i>	
GPS tracks from the Bicycle Counting Week 2016	(Cycling Intelligence, 2021)
Hourly bicycle counts from temporary and permanent count stations	(Municipality of Amsterdam, 2016; Municipality of The Hague, 2019; Municipality of Utrecht, 2020; NDW Dexter, 2022)
Hourly motorised vehicle counts from temporary and permanent count stations	(Municipality of Amsterdam, 2016; NDW Dexter, 2022)
Transport models	(Metropolitan Region Rotterdam The Hague, 2021; Municipality of Amsterdam, 2022; Municipality of Utrecht, 2018)
<i>Infrastructural data</i>	
Base network	(Rijkswaterstaat, 2019)
Speed limits	(Metropolitan Region Rotterdam The Hague, 2021; Rijkswaterstaat, 2020b)
Cycling infrastructure, intersection types, and grade-separated road sections	(Dutch Cyclists' Union, 2020)
<i>Destinations</i>	
Commercial facilities (e.g. shops, restaurants, bars) and office buildings	(Kadaster, 2022)
Shopping areas and office areas	(Province of North-Holland, 2022; Province of South-Holland, 2022; Province of Utrecht, 2018)
Railway station entries	(Dutch Cyclists' Union, 2020)
Educational facilities (primary schools, secondary schools, vocational education, higher professional education, and universities)	(DUO, 2022)

selection of the 30 km/h roads. The transport model of Rotterdam and The Hague includes a higher number of 30 km/h roads, in particular in The Hague.

Two categories of cycling infrastructure are distinguished in this study: separated bicycle tracks and on-street cycling facilities. The on-street cycling facilities are a combination of roadways with mixed traffic conditions and bicycle lanes. These are combined as cyclists share the road with motorised vehicles at both infrastructure types. This is justified as several studies found no added safety effects of bicycle lanes relative to mixed traffic conditions (Mulvaney et al., 2015; van Petegem et al., 2021).

Last, four types of destinations are distinguished: commercial facilities in shopping areas, office buildings in office areas, railway station entries, and educational facilities. Service areas around these destinations are calculated based on 150 metre network distance to these destinations to account for the effect of the destinations on safety (Ulak et al., 2018).

### **3.4. Variation in the predictors and crashes**

Another consequence of using such a variety of datasets is that this leads to local differences caused by the availability of data. [Appendix 1](#) shows the variation in descriptive statistics of the predictors between the cities. The total network exposure to cyclists is lower than the total network exposure to motorised vehicles in all cities, except Rotterdam. Furthermore, Amsterdam has most grade-separated road sections. This is related to the large number of canals in the city centre of Amsterdam and that nearly all road sections in the city centre are available in the data. The city centre of Amsterdam is also relatively large, which results in nearly half of the analysed road sections being located within 150 metres from a commercial facility.

[Table 3](#) shows that, in absolute numbers, bicycle crashes in the data vary over the cycling infrastructure types. Most crashes occurred on the 50 km/h roads with separated bicycle tracks. However, the number of crashes per kilometre on 50 km/h roads with on-street cycling facilities is higher (except Utrecht). When looking to the 30 km/h roads with separated bicycle tracks, the number of crashes per kilometre is relatively high compared to the 30 km/h roads with on-street cycling facilities.

Additionally, [Table 3](#) also shows that a large share of the bicycle crashes in the data occurred close to commercial facilities. Especially in Amsterdam, the number of crashes per kilometre close to commercial facilities is high. The number of crashes per kilometre in office areas varies per city, as, for example, this is low in Amsterdam and high in Rotterdam. Furthermore, in Amsterdam, Utrecht, and Rotterdam the number of

**Table 3.** Total number of crashes in 2015–2019, share of crashes, and crashes per kilometre per type of cycling infrastructure and within 150 metres of selected destinations.

Variable	Amsterdam			Utrecht			Rotterdam			The Hague		
	n	%	Crash /km	n	%	Crash /km	n	%	Crash /km	n	%	Crash /km
<i>Cycling infrastructure</i>												
50 km/h, separated	863	67.6	2.55	287	55.1	1.55	588	50.4	1.65	778	45.7	2.02
50 km/h, on-street	242	19.0	4.32	68	13.0	1.12	220	18.8	2.25	407	23.9	2.81
30 km/h, separated	45	3.5	4.68	66	12.7	3.72	68	5.8	1.64	56	3.3	1.58
30 km/h, on-street	126	9.9	2.47	100	19.2	1.09	304	26.0	1.05	514	30.2	0.82
Total	1,276	100.0	2.80	521	100.0	1.47	1,167	100.0	1.50	1,701	100.0	1.44
<i>Destinations within 150 m</i>												
Comm. facilities	913	71.5	4.12	274	52.6	2.29	653	55.9	2.29	777	45.7	2.23
Other	363	28.4	1.56	247	47.4	0.74	514	44.0	1.04	924	54.3	11.1
Total	1,276	100.0	2.80	521	100.0	1.47	1,167	100.0	1.50	1,701	100.0	1.44
Office buildings	154	12.1	1.94	196	37.6	1.99	285	24.4	2.68	230	13.5	1.55
Other	1,122	87.9	2.99	325	62.4	1.27	882	75.6	1.31	1,471	86.5	1.43
Total	1,276	100.0	2.80	521	100.0	1.47	1,167	100.0	1.50	1,701	100.0	1.44
Rail. station entries	24	1.9	3.00	28	5.4	2.79	21	1.8	1.62	11	0.6	1.26
Other	1,252	98.1	2.80	493	94.6	1.43	1,146	98.2	1.50	1,690	99.3	1.44
Total	1,276	100.0	2.80	521	100.0	1.47	1,167	100.0	1.50	1,701	100.0	1.44
Educ. facilities	408	32.0	2.82	168	32.2	1.70	365	31.3	1.54	290	17.0	1.34
Other	868	68.0	2.80	353	67.7	1.38	802	68.7	1.48	1,411	82.9	1.47
Total	1,276	100.0	2.80	521	100.0	1.47	1,167	100.0	1.50	1,701	100.0	1.44

Note: Separated is separated bicycle tracks; on-street is on-street cycling facilities; Comm. is commercial; Rail. is railway; Educ. is educational.

crashes per kilometre within 150 metres of railway station entries and of educational facilities is slightly higher than further away.

## 4. Methodology

### 4.1. Estimating network-wide hourly exposure

Network-wide hourly exposure to cyclists is estimated by calibrating the hourly bicycle GPS data with temporary and permanent count station measurements. For this calibration, support vector regression models were developed for the four cities based on the approach utilised by Uijtdewilligen et al. (2022) for the city of Utrecht. For motorised vehicles, the average relative hourly volumes from the count station data are multiplied by the estimated weekly average volumes obtained from the transport models of the study areas. The hourly motorised vehicle volumes are estimated separately for roads with 30 km/h and 50 km/h speed limits, allowing a more detailed estimation of exposure to motorised vehicles compared to the approach by Uijtdewilligen et al. (2022).

### 4.2. Betweenness centrality

In this study, the effect of centrality on bicycle safety is modelled by the betweenness centrality indicator (Freeman, 1978). A high betweenness centrality means that a node (i.e. a road section in this case) in the network

links several other nodes (Gil, 2017; Kamel & Sayed, 2021; Zhang et al., 2015). In this way, road sections that serve as a major connector in the entire network are identified, illustrating the degree of a network being reliant on a number of road sections (Zhang et al., 2015). This would imply that large shares of traffic have to follow the same road sections to move between an origin and destination. The Urban Network Analyst Toolbox for ArcMap is used to calculate the betweenness centrality (Sevtsuk et al., 2016).

**4.3. Modelling of bicycle crash risk**

As crashes are rare events, the number of zeros in a dataset is relatively high when analysing crash data. It is common in the literature to analyse the total number of crashes over the years. However, this study disaggregates the crash observations into hours of the days of the week, leading to 168 observation units (i.e.  $7 \times 24$ ) per road section rather than 1 unit (i.e. total number of crashes over the years). This finer temporal resolution leads to a very large number of zeros as the crash numbers are distributed over more observation units. As a result, the majority of observation units have zero crashes, whereas most of the remaining units have only one crash (Table 4).

This preponderance of zeros and ones makes the bicycle crashes virtually a binary variable, as there is either a crash or no crash. Therefore, a binary dependent variable model, namely logistic regression, is used to estimate the crash probabilities (Washington et al., 2011). The parameters are estimated using maximum likelihood estimation and are used to estimate the probability of observing at least one bicycle crash, as some observation units have more than one crash, as in Kim et al. (2010). This probability is called “bicycle crash risk” and it is used in the rest of this paper. Since the response variable consists of rare events, the predicted probabilities are relatively low and mainly on the left tail of the distribution, the logarithmic part of the equation. These low probabilities result from the model when the numerator is very low, making the denominator close to 1. In this way, the interpretation of the estimated coefficients of the logistic regression model is similar to generalised linear models (GLMs) for count data: Poisson regression and its extension negative binomial regression

**Table 4.** The number of observation units with one, two, three, and zero crashes per city.

	1 crash	2 crashes	3 crashes	Total	0 crashes
Amsterdam	1,258	9	0	1,276	365,300
Utrecht	511	5	0	521	323,383
Rotterdam	1,148	8	1	1,167	716,025
The Hague	1,681	10	0	1,701	1,654,947
<i>Total</i>	<i>4,598</i>	<i>32</i>	<i>1</i>	<i>4,665</i>	<i>3,059,655</i>

(Mittlböck & Heinzl, 2001). The results of the logistic regression models and the negative binomial regression model in this study are considered sufficiently similar to allow a comparison between these models.

Apart from the exposure variables, several other variables are included in the analysis. To further explore the temporal effects in crashes, the *evening/night (18:00–06:00)* variable indicating time of day is used with *morning/day (06:00–18:00)* as reference. The effects of network structure are examined using three types of variables: *betweenness centrality*, *intersection density*, and *grade-separated road sections*. Furthermore, two types of *cycling infrastructure* on roads with different *speed limits* are compared to investigate the safety difference between infrastructure types where cyclists are separated from motorised vehicles and where they share the road, with *30 km/h roads with on-street cycling facilities* as reference. Moreover, road sections that are within 150 metres network distance from *commercial facilities*, *office buildings*, *railway station entries*, and *educational facilities* are identified by means of dummy variables to account for the effect of these destinations on safety. Last, to identify whether there are unobserved city-specific factors, a variable indicating in which *municipality* a road section is located is used, with *Rotterdam* as reference.

## 5. Results and discussion

### 5.1. Hourly vs. daily average approach

To verify the use of an hourly approach rather than a daily average approach, three models are fitted: a logistic regression model with hourly disaggregation of bicycle crashes and exposure variables, a logistic regression model with daily averages of the exposure variables, and a negative binomial regression model with aggregated crash frequencies and daily averages of the exposure variables. The data from all four cities are combined for these models. The results are presented in [Table 5](#).

When comparing the two daily average models, there are only some minor, negligible differences between the estimated parameters. On the other hand, when comparing the daily average models with the hourly model, the most remarkable results are as follows:

- the results imply that the daily average models underestimate the effect of the exposure to motorised vehicles on bicycle safety and overestimate the impact of exposure to cyclists;
- the importance of separated bicycle tracks on 50 km/h roads is underestimated by the daily average models;
- the results of 50 km/h roads with on-street cycling facilities is inconsistent.

**Table 5.** Coefficient estimates of the hourly and daily average models for the effects of selected risk factors on bicycle safety.

	Hourly model (LR) Coeff. (s.e.)	Daily average model (LR) Coeff. (s.e.)	Daily average model (NB) Coeff. (s.e.)
(Intercept)	<b>-8.93</b> (0.07)***	<b>-7.00</b> (0.20)***	<b>-6.63</b> (0.17)***
<i>Exposure</i>			
Exp. to cyclists (log)	<b>0.47</b> (0.02)***	<b>0.65</b> (0.03)***	<b>0.61</b> (0.03)***
Exp. to motorised vehicles (log)	<b>0.28</b> (0.01)***	<b>0.13</b> (0.02)***	<b>0.11</b> (0.02)***
<i>Temporal (ref = morning/day 06:00-18:00)</i>			
Evening/night 18:00-06:00	<b>-0.50</b> (0.03)***	-	-
<i>Network structure</i>			
Betw. centrality (normalised)	<b>4.72</b> (0.84)***	<b>6.52</b> (1.40)***	<b>5.76</b> (1.17)***
Sign. intersection density (scaled)	<b>0.31</b> (0.02)***	<b>0.30</b> (0.03)***	<b>0.32</b> (0.03)***
Roundabout density (scaled)	<b>0.21</b> (0.02)***	<b>0.22</b> (0.03)***	<b>0.22</b> (0.02)***
Unsig. intersection density (scaled)	<b>0.39</b> (0.02)***	<b>0.41</b> (0.03)***	<b>0.39</b> (0.03)***
Grade-separated road sections	0.00 (0.05)	0.01 (0.08)	0.01 (0.07)
<i>Cycling infrastructure (ref = 30 km/h, on-street cycling facilities)</i>			
50 km/h, separated bicycle tracks	<b>-0.46</b> (0.05)***	<b>-0.19</b> (0.07)**	<b>-0.10</b> (0.06)
50 km/h, on-street cycling facilities	0.04 (0.05)	<b>0.24</b> (0.07)**	<b>0.25</b> (0.06)***
30 km/h, separated bicycle tracks	<b>0.18</b> (0.07)*	0.12 (0.11)	<b>0.22</b> (0.10)*
<i>Destinations within 150 metres</i>			
Commercial facilities	<b>0.60</b> (0.03)***	<b>0.55</b> (0.04)***	<b>0.56</b> (0.04)***
Office buildings	0.04 (0.04)	0.00 (0.06)	0.01 (0.05)
Railway station entries	-0.08 (0.11)	-0.16 (0.18)	-0.03 (0.15)
Educational facilities	0.02 (0.03)	<b>0.14</b> (0.05)**	0.05 (0.05)
<i>Unobserved city-specific factors (ref = Rotterdam)</i>			
Amsterdam	<b>1.20</b> (0.05)***	<b>1.41</b> (0.08)***	<b>1.32</b> (0.07)***
Utrecht	<b>0.66</b> (0.06)***	<b>0.95</b> (0.09)***	<b>0.82</b> (0.08)***
The Hague	<b>0.97</b> (0.05)***	<b>1.25</b> (0.08)***	<b>1.17</b> (0.07)***
Num. obs.	3,063,816	18,237	18,237
Log Likelihood	-31,819	-7,211	-10,055
Likelihood ratio $\chi^2$ (df = 18; 17; 17)	5,770***	1,862***	2,177***
Deviance	63,638	14,421	9,540
AIC	63,676	14,457	20,147

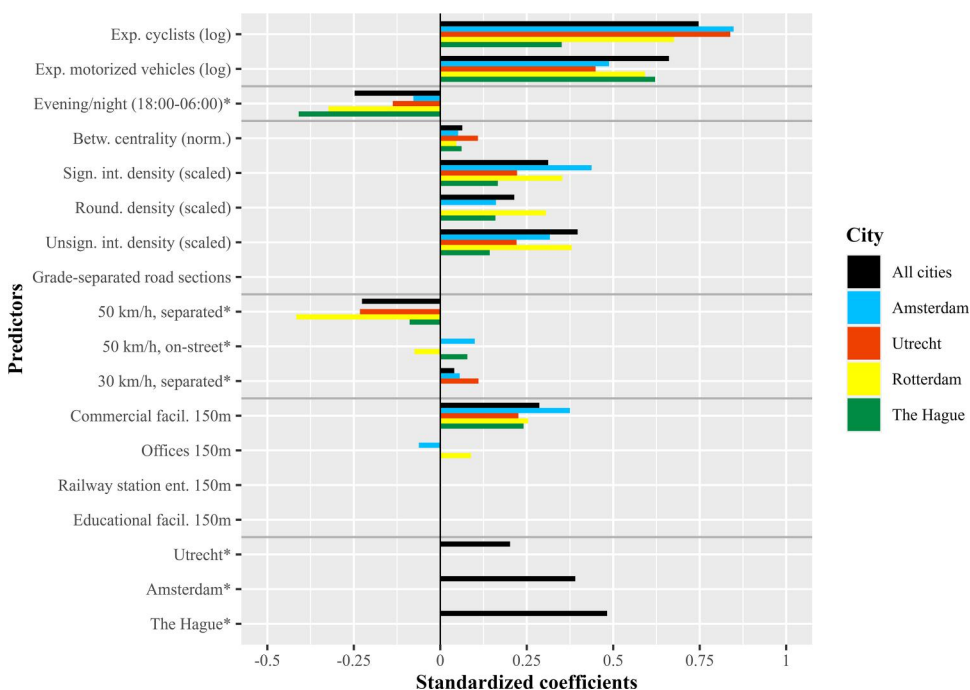
Note: \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ ; · $p < 0.1$ ; bold values are significant at least at the 10% level; LR is logistic regression; NB is negative binomial regression; Coeff. is coefficient; s.e. is standard error; Exp. is exposure; Betw. is betweenness; Sign. is signalised; Unsig. is unsignalised.

Moreover, the municipality variable is significant for all cities, which implies that there are unobserved city-specific factors (e.g. urban design) that affect the results. Amsterdam, Utrecht, and The Hague significantly differ from Rotterdam, which might be caused by Rotterdam having a newer network than the other cities and, to some extent, by using a wide range of data sources.

### 5.2. Main findings and discussion

The results in Table 5 show that there are substantial differences between the daily average models and the hourly model. Given the refined resolution of the hourly model, the remainder of this section discusses the hourly results. Moreover, some significant differences among the four studied cities are identified; therefore, results of city-specific hourly models are also presented. However, it is noteworthy that, despite the large variety of data sources (that may cause these differences to some extent), most





**Figure 3.** Standardised coefficient estimates of the five logistic regression models (dependent variable is presence of a crash (0 or 1) at a road section at a given hour).

\*Reference: for evening/night (18:00–06:00) is morning/day (06:00–18:00); for cycling infrastructure is 30 km/h, on-street cycling facilities; for municipality is Rotterdam.

Note: Exp. is exposure; Betw. is betweenness; norm. is normalised; Sign. is signalised; int. is intersection; Round. is roundabout; Unsign. is unsignalised; separated is separated bicycle tracks; on-street is on-street cycling facilities; facil. is facilities; offices is office buildings; ent. is entries.

results are quite robust across the cities. The probability of observing at least one crash on a road section at a given hour is modelled using logistic regression. This probability is called "bicycle crash risk," which is used in the rest of the paper. Figure 3 shows the standardised coefficient estimates for the significant variables of the combined model and the four city-specific models (please see Appendix 2 for full regression tables). The standardised coefficients help to compare the direction and the magnitude of the impact of variables (Nieminen et al., 2013).

### 5.2.1. Effects of exposure on bicycle safety

Both the *exposure to cyclists* and the *exposure to motorised vehicles* show a strong impact on bicycle safety in all cities. The results indicate that hours with larger exposure levels lead to a higher bicycle crash risk. Furthermore, it can be noticed that a relative increase in the exposure to cyclists has a slightly larger impact than the same relative increase in exposure to motorised vehicles. This difference between the exposure to cyclists and motorised vehicles contradicts findings in other studies. For example,

Uijtdewilligen et al. (2022) found that, after aggregating exposure in the whole network, an increase in exposure to motorised vehicles has a larger effect on bicycle crash frequency than exposure to cyclists. This shows that spatial aggregation of traffic exposure might be leading to imbalanced exposure metrics. Moreover, a study in London, that also used logistic regression, found a comparable effect for the exposure to motorised vehicles on crash probability, but a lower effect for exposure to cyclists (Aldred et al., 2018). This might be due to the difference in cycling levels between Dutch cities and London. Last, Ferster et al. (2021) also investigated temporal variation in the exposure to cyclists and bicycle safety and found increased crash hotspots during peak hours, implying a heterogeneous distribution of bicycle crashes throughout the day similar to findings in our study. This is related to the result that bicycle crash risk is lower during the *evening/night hours* (18:00–06:00) than during the *morning/day hours* (06:00–18:00). Previously, Uijtdewilligen et al. (2022) found that night time is more risky for cyclists when controlling for exposure; however, this study spatially aggregated the whole network. Therefore, it can be argued that disaggregation of the network both spatially and temporally would lead to more precise results indicating that night hours might be less risky than the daytime hours.

### **5.2.2. Relationship between network structure and bicycle safety**

The *betweenness centrality* variable has a relatively low impact on bicycle safety and results imply that the more central the road section is, the slight higher the bicycle crash risk. One reason might be that at road sections with high centrality, many routes come together, leading to increased interactions and conflicts between road users. These results contradict the findings of previous studies, which are mainly from North America (Kamel & Sayed, 2021; Zhang et al., 2015). However, the findings of North American studies may not be comparable in this case, as most networks of North American cities have a grid pattern, while the networks of the cities in the present study are located in old, dense city centres without space for infrastructure.

The *intersection density* variables have an average impact on bicycle safety. The results indicate that bicycle crash risk is higher where there are more intersections per kilometre. Different transport modes interact with each other at such locations, which might lead to increased crash risk. These findings are consistent with the literature (Nashad et al., 2016; Osama & Sayed, 2016; Wei & Lovegrove, 2013).

It was expected that road users are, to some extent, forced to use *grade-separated road sections* to pass, for example, rivers, canals, or railways. This may increase the number of conflicts, as was found in other studies

(Vandenbulcke et al., 2014; Wang, De Backer et al., 2019). However, in our study, no significant relationship is found between bicycle crash risk and grade-separated road sections.

### **5.2.3. Cycling infrastructure and safety**

For the *cycling infrastructure* variable, the results indicate that bicycle crash risk on 50 km/h roads with separated bicycle tracks is lower than the reference (30 km/h roads with on-street cycling facilities). This might be caused by the fact that for three out of the four cities only the higher volume 30 km/h roads are included and that such roads may have negative implications for bicycle safety. Nevertheless, the safety benefits of separated bicycle tracks on 50 km/h roads were also found in other studies (DiGioia et al., 2017; Prato et al., 2016; Thomas & De Robertis, 2013; van Petegem et al., 2021).

Second, no significant relationship between 50 km/h roads with on-street cycling facilities and bicycle crash risk is found. This implies that no additional effect of this road type on safety is found compared to the reference. However, this result may be caused by the contradictory city-specific findings, as bicycle crash risk on this road type is higher than the reference in Amsterdam and The Hague, it is lower in Rotterdam, and in Utrecht no significant relationship is found. This inconsistency is also found when comparing findings of existing studies (DiGioia et al., 2017; Mulvaney et al., 2015).

Last, the results show higher crash risk at 30 km/h roads with separated bicycle tracks compared to the reference, but the impact on bicycle safety is low. Although the share of this road type is limited ([Appendix 1](#)), it is surprising that separated bicycle tracks on lower speed roads increase bicycle crash risk. Presumably, these roads are designed as 50 km/h roads with separated bicycle tracks, which may cause speeding as the design does not fit the intended speed limit (SWOV, 2018).

### **5.2.4. The effect of destinations on bicycle safety**

It is shown that cycling within 150 metres network distance of commercial facilities has a relatively strong impact on bicycle safety. The findings imply that in shopping areas bicycle crash risk is higher, presumably due to increased numbers of pedestrians or other road users. Both Merlin et al. (2020) and Mukoko and Pulugurtha (2020) identified that cyclists are significantly more often involved in a crash when cycling through commercial areas. Moreover, Ferster et al. (2021) found that during the off-peak hours and in the weekends bicycle crash hotspots are often located on

commercial streets, while during the peak hours on weekdays these hot-spots are more located in areas with more commuter cyclists.

Previous studies found higher crash risk around business areas (Ferster et al., 2021; Williams et al., 2018), arguing that business areas have increased complexity due to higher concentrations of on-street parking, a higher turnover rate of vehicles, and a busier road environment compared to other area types. However, no significant effect of offices on bicycle crash risk is found in this study.

For both railway station entries and educational facilities, no significant relationship with bicycle crash risk is found, meaning that no additional effect of these destinations on bicycle safety is found in this study. Note that this does not imply that the areas around these facilities are safer for cyclists. One might argue that at certain times of the day railway station entries and educational facilities attract large flows of different modes of transport. This may cause complex situations and leads to potential conflicts between these different flows of traffic, which is already captured by the exposure variables. Loidl et al. (2016), for example, found bicycle crash peaks during certain hours of the day in areas with a high concentration of schools. Furthermore, Schepers (2021) showed that on road sections within closer range of schools and railway stations (limited effect) the number of injury and fatal crashes per 100,000 inhabitants is higher.

### ***5.3. Limitations and future research directions***

One limitation of this study is the accuracy of the bicycle volume estimates, which might affect the results of Rotterdam in particular as the accuracy of the bicycle volume estimates is lower compared to the other cities. The lower number of available GPS tracks and the count stations being located at the most busy road sections for cyclists may cause this lower accuracy in Rotterdam. Consequently, the bicycle volumes at less busy roads have a higher chance of being overpredicted, which eventually affects the accuracy of the coefficient for the exposure to cyclists. To prevent such overprediction, bicycle count stations should be more equally divided over the cycling network.

Second, the transport model of The Hague is far more complete compared to the other cities. Complete in this sense means that nearly all 30 km/h roads are available, whereas in the other cities only the higher-volume 30 km/h roads are in the transport model. To minimise the effect of this inconsistency on the results, it is chosen to emphasise the results of the combined model rather than the city-specific models. Relying on the available data is a common problem for case study-specific studies and affects the

transferability of findings. It is therefore recommended to include more complete transport models in future studies and to combine data from multiple cities in order to prevent data issues.

Third, in this study, the spatial and temporal character of bicycle crashes is dealt with by using highly detailed spatially and temporally disaggregated exposure data. However, the modelling approach in this study excludes unobserved heterogeneities and spatial and temporal autocorrelations. Nonetheless, the similarities in the findings of different cities imply the consistency of the results against modelling choice; thus, utilisation of more complex modelling techniques considering spatial and temporal heterogeneity may make no dramatic changes. Nevertheless, to have a more in-depth understanding of the relationship between the examined crash risk factors and bicycle safety, future studies may use more complex models, as utilised by Guo, Li et al. (2018) and Guo, Osama et al. (2018), to deal with spatial and temporal heterogeneity.

Last, it is noteworthy that the crash data used in this study is prone to underreporting, which is a common problem of using police reported data for bicycle crashes. In particular, crashes not involving motorised vehicles are underreported, as often only an ambulance attends such crash sites or cyclists seek emergency care themselves. Consequently, only the severe bicycle crashes and crashes involving a motorised vehicle are reported by the police; thus, bicycle crashes are underrepresented, which likely affects the results (Derriks & Mak, 2007; Wegman et al., 2012). To solve some of the underreporting problems, ambulance reported data can be used in addition to the police reported data. As ambulances also attend crash sites of cyclists where the police are unable to attend, the ambulance reported data may show more complete crash figures. However, at the moment the ambulance data for the study area are unavailable for research.

## 6. Conclusions

This study aims to contribute to safer urban cycling by examining bicycle crash risk factors in Dutch cities. The probability of observing at least one crash on a road section at a given hour is modelled using logistic regression. This probability is called "bicycle crash risk" in this paper. A highly detailed spatiotemporal approach is used to examine bicycle crash risk by combining data of the four largest Dutch cities. It is noteworthy that, despite the large variety of data sources, the results are quite robust across the cities. This helps to confirm the findings and provides the transferability and generalisability of the combined model. Moreover, using a fine spatiotemporal resolution in examining the risk factors helps investigate where and when bicycle crashes tend to occur. Another strength of the study is

that this detailed level of spatiotemporal disaggregation at the scale of four major cities is very scarce in the literature. The main findings of the study are highlighted as follows:

1. Adopting an hourly approach gives more detailed results compared to models using daily average crash figures and exposure metrics.
2. The exposure variables (cyclist and motorised vehicles) have the largest effect on bicycle crash risk.
3. Bicycle crash risk is lower during the evening and night hours than during the daytime hours.
4. The most central road sections (i.e. betweenness centrality) in the cycling network have a higher bicycle crash risk, but the overall impact of centrality is limited.
5. The higher the intersection density, the higher the bicycle crash risk.
6. Compared to 30 km/h roads with on-street cycling facilities, bicycle crash risk on 50 km/h roads with separated bicycle tracks is lower.
7. 30 km/h roads with separated bicycle tracks have a higher bicycle crash risk than 30 km/h roads with on-street cycling facilities, but the impact on bicycle safety is limited.
8. Roads close to commercial facilities have a higher bicycle crash risk than roads further. The impact of commercial facilities on bicycle safety is relatively high.

The second conclusion shows that it is important for local policymakers to take measures to safely manage large flows of cyclists. This is also related to the sixth conclusion, where it becomes evident that, after correcting for exposure, separating cyclists from high speed motorised vehicles has larger impact on bicycle safety than mixing cyclists with motorised vehicles on high-volume 30 km/h roads. This has implications for the current debate about decreasing the speed limit to 30 km/h inside urban areas, as the findings suggest that it is safer to implement separated bicycle tracks on 50 km/h roads than to decrease the speed limit to 30 km/h. Additionally, conclusion seven implies that just decreasing the speed limit from 50 km/h to 30 km/h on roads with separated bicycle tracks may not be enough to improve safety of cyclists. More infrastructural measures are necessary to decrease the operating speed of motorised vehicles. Conclusion eight shows that cycling through commercial areas with high numbers of road users (e.g. pedestrians) needs attention too, since cyclists are at more risk in such areas. In general, the results indicate that concerns about the effects of increasing bicycle use and large flows of motorised vehicles on bicycle crashes are valid and emphasise the importance of further improving bicycle safety in cities.



## Acknowledgments

The authors thank the *Fietzersbond* (Dutch Cyclists' Union) for sharing their very rich bicycle network dataset. We also thank the municipalities and the Metropolitan Region Rotterdam The Hague for sharing their transport models and count data.

## Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Note

1. Bicycle priority streets are a special type of access road, designed for large flows of cyclists and functioning as important connection for cyclists. Car traffic is allowed, but to a limited extent, at low speeds, and they are inferior to cyclists.

## Funding

This work was financially supported by the Dutch Ministry of Infrastructure and Water Management. The opinions, results, and findings expressed in this manuscript are those of the authors and do not necessarily represent the views of the aforementioned organisations.

## ORCID

Teun Uijtdewilligen  <http://orcid.org/0000-0002-7156-8010>

Mehmet Baran Ulak  <http://orcid.org/0000-0002-0893-3871>

Frits Bijleveld  <http://orcid.org/0000-0002-5403-0438>

Karst T. Geurs  <http://orcid.org/0000-0003-0918-8903>

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Appendix 1. The city-specific descriptive statistics of the predictors.

	Amsterdam						Utrecht						Rotterdam						The Hague					
	N	Mean	SD	Min	Max	Total	N	Mean	SD	Min	Max	Total	N	Mean	SD	Min	Max	Total	N	Mean	SD	Min	Max	Total
<i>Exposure</i>	<i>hours</i>						<i>hours</i>						<i>hours</i>						<i>hours</i>					
Exp. to cyclists	366,576	24.68	43.84	0.14	1,333	9,047,440	323,904	18.64	46.66	0.15	2,011	6,037,510	717,192	79.81	182.74	0.86	9,680	57,242,173	1,656,648	6.71	10.03	0.01	598	11,120,696
Exp. to motorised vehicles	366,576	53.03	119.47	0.01	3,005	19,440,162	323,904	44.30	98.50	0.01	1,891	14,349,623	717,192	36.25	86.67	0.01	2,551	25,999,624	1,656,648	16.08	47.16	0.00	2,301	26,638,850
<i>Temporal</i>	<i>hours</i>						<i>hours</i>						<i>hours</i>						<i>hours</i>					
Daytime	366,576	0.50	0.50	0	1	183,288	323,904	0.50	0.50	0	1	161,952	717,192	0.50	0.50	0	1	358,596	1,656,648	0.50	0.50	0	1	828,324
Night time	366,576	0.50	0.50	0	1	183,288	323,904	0.50	0.50	0	1	161,952	717,192	0.50	0.50	0	1	358,596	1,656,648	0.50	0.50	0	1	828,324
<i>Network structure</i>	<i>road sections</i>						<i>road sections</i>						<i>road sections</i>						<i>road sections</i>					
Length in km	2,182	0.21	0.27	0.00	2.64	455.02	1,928	0.18	0.21	0.00	1.97	355.35	4,269	0.18	0.22	0.00	3.09	778.10	9,861	0.12	0.13	0.00	2.18	1178.50
Betw. Centrality (norm.)	2,182	0.01	0.01	0.00	0.09		1,928	0.01	0.02	0.00	0.19		4,269	0.01	0.01	0.00	0.17		9,861	0.01	0.01	0.00	0.18	
Sign. int. density (scaled)	2,182	0.02	1.02	-0.49	6.38		1,928	0.02	1.02	-0.45	8.28		4,269	0.01	1.01	-0.31	9.04		9,861	0.002	1.00	-0.26	11.26	
Round. density (scaled)	2,182	0.01	1.02	-0.26	16.25		1,928	0.01	1.02	-0.24	11.59		4,269	0.01	1.01	-0.26	11.21		9,861	0.001	1.00	-0.15	21.51	
Unsig. int. density (scaled)	2,182	0.01	1.02	-0.47	10.87		1,928	0.01	1.03	-0.48	12.13		4,269	0.01	1.01	-0.57	7.99		9,861	0.003	1.00	-0.57	36.61	
Grade-separated road sections	2,182					444	1,928				97	4,269				302	9,861					312		
<i>Cycling infrastructure</i>	<i>km (prop.)</i>						<i>km (prop.)</i>						<i>km (prop.)</i>						<i>km (prop.)</i>					
50 km/h, separated	1,622	0.21	0.29	0.00	2.64	338.37 (0.74)	1,152	0.16	0.20	0.00	1.97	185.00 (0.52)	2,080	0.17	0.23	0.00	3.09	356.77 (0.46)	3,388	0.11	0.13	0.00	1.69	385.61 (0.33)
50 km/h, on-street	289	0.19	0.25	0.01	1.55	56.03 (0.12)	246	0.25	0.24	0.01	1.56	60.75 (0.17)	620	0.16	0.18	0.01	1.68	97.66 (0.12)	1,529	0.09	0.10	0.00	1.33	145.06 (0.12)
30 km/h, separated	41	0.23	0.22	0.01	0.63	9.61 (0.02)	145	0.12	0.20	0.01	1.53	17.76 (0.05)	366	0.11	0.17	0.00	1.23	41.36 (0.05)	393	0.09	0.15	0.00	1.29	35.52 (0.03)
	230	0.22	0.20	0.01	1.22	51.02 (0.11)	385	0.24	0.22	0.01	1.41	91.84 (0.26)	1,249	0.23	0.23	0.01	2.81	288.33 (0.37)	4,696	0.13	0.12	0.00	2.18	627.22 (0.53)

(continued)



Continued.

	Amsterdam					Utrecht					Rotterdam					The Hague									
	N	Mean	SD	Min	Max	Total	N	Mean	SD	Min	Max	Total	N	Mean	SD	Min	Max	Total	N	Mean	SD	Min	Max	Total	
30 km/h, on-street																									
Destination within 150m						<i>km (prop.)</i>						<i>km (prop.)</i>												<i>km (prop.)</i>	
Commercial facilities	1,042	0.21	0.25	0.00	1.90	221.69 (0.49)	600	0.20	0.21	0.00	1.95	119.42 (0.34)	1,664	0.17	0.17	0.00	1.48	285.04 (0.37)	3,132	0.11	0.09	0.00	0.81	347.65 (0.29)	
Office buildings	335	0.24	0.30	0.01	2.16	79.47 (0.17)	526	0.19	0.24	0.00	1.97	98.66 (0.28)	629	0.17	0.19	0.01	1.66	106.46 (0.14)	1,154	0.13	0.13	0.01	1.01	148.04 (0.13)	
Railway station entries	24	0.33	0.29	0.02	1.01	7.99 (0.02)	64	0.16	0.18	0.01	0.97	10.04 (0.03)	78	0.17	0.16	0.00	0.64	12.98 (0.02)	71	0.12	0.12	0.01	0.59	8.71 (0.01)	
Educational facilities	459	0.32	0.30	0.01	1.90	144.76 (0.32)	432	0.23	0.23	0.01	1.95	98.74 (0.28)	1,235	0.19	0.17	0.00	1.40	237.28 (0.30)	1,633	0.13	0.11	0.00	0.75	215.81 (0.18)	

Appendix 2. Coefficient estimates of the four city-specific logistic regression models for the effects of selected risk factors on bicycle crash risk.

	Amsterdam <i>Coeff. (s.e.)</i>	Utrecht <i>Coeff. (s.e.)</i>	Rotterdam <i>Coeff. (s.e.)</i>	The Hague <i>Coeff. (s.e.)</i>
(Intercept)	<b>-8.23</b> (0.13) <sup>***</sup>	<b>-8.32</b> (0.16) <sup>***</sup>	<b>-8.65</b> (0.13) <sup>***</sup>	<b>-7.69</b> (0.07) <sup>***</sup>
<i>Exposure</i>				
Exp. to cyclists (log)	<b>0.52</b> (0.03) <sup>***</sup>	<b>0.55</b> (0.04) <sup>***</sup>	<b>0.47</b> (0.03) <sup>***</sup>	<b>0.30</b> (0.03) <sup>***</sup>
Exp. to motorised vehicles (log)	<b>0.26</b> (0.03) <sup>***</sup>	<b>0.19</b> (0.03) <sup>***</sup>	<b>0.30</b> (0.03) <sup>***</sup>	<b>0.27</b> (0.02) <sup>***</sup>
<i>Temporal</i>				
Evening/night 18:00-06:00	<b>-0.16</b> (0.06) <sup>*</sup>	<b>-0.27</b> (0.10) <sup>**</sup>	<b>-0.65</b> (0.07) <sup>***</sup>	<b>-0.82</b> (0.06) <sup>***</sup>
<i>Network structure</i>				
Betw. centrality (normalised)	<b>3.87</b> (1.83) <sup>*</sup>	<b>6.05</b> (1.86) <sup>**</sup>	<b>3.17</b> (1.69)	<b>5.30</b> (1.49) <sup>***</sup>
Sign. intersection density (scaled)	<b>0.43</b> (0.05) <sup>***</sup>	<b>0.22</b> (0.08) <sup>**</sup>	<b>0.35</b> (0.04) <sup>***</sup>	<b>0.17</b> (0.03) <sup>***</sup>
Roundabout density (scaled)	<b>0.16</b> (0.07) <sup>*</sup>	0.08 (0.12)	<b>0.30</b> (0.05) <sup>***</sup>	<b>0.16</b> (0.02) <sup>***</sup>
Unsig. intersection density (scaled)	<b>0.31</b> (0.05) <sup>***</sup>	<b>0.21</b> (0.08) <sup>**</sup>	<b>0.37</b> (0.05) <sup>***</sup>	<b>0.14</b> (0.02) <sup>***</sup>
Grade-separated road sections	0.03 (0.06)	0.06 (0.15)	-0.05 (0.10)	-0.10 (0.13)
<i>Cycling infrastructure (ref = 30 km/h, on-street cycling facilities)</i>				
50 km/h, separated bicycle tracks	-0.17 (0.11)	<b>-0.47</b> (0.13) <sup>***</sup>	<b>-0.83</b> (0.09) <sup>***</sup>	<b>-0.19</b> (0.08) <sup>*</sup>
50 km/h, on-street cycling facilities	<b>0.29</b> (0.12) <sup>*</sup>	-0.09 (0.16)	<b>-0.22</b> (0.10) <sup>*</sup>	<b>0.22</b> (0.08) <sup>**</sup>
30 km/h, separated bicycle tracks	<b>0.41</b> (0.18) <sup>*</sup>	<b>0.42</b> (0.17) <sup>*</sup>	-0.16 (0.14)	0.11 (0.14)
<i>Destinations within 150 metres</i>				
Commercial facilities	<b>0.75</b> (0.07) <sup>***</sup>	<b>0.49</b> (0.10) <sup>***</sup>	<b>0.52</b> (0.06) <sup>***</sup>	<b>0.52</b> (0.05) <sup>***</sup>
Office buildings	<b>-0.17</b> (0.09)	0.12 (0.10)	<b>0.25</b> (0.07) <sup>***</sup>	-0.05 (0.07)
Railway station entries	0.17 (0.21)	-0.14 (0.21)	-0.08 (0.22)	-0.30 (0.31)
Educational facilities	0.03 (0.06)	0.06 (0.10)	-0.02 (0.07)	0.04 (0.07)
Num. obs.	366,576	323,904	717,192	1,656,648
Log Likelihood	-7,711	-3,504	-7,988	-12,549
Likelihood ratio $\chi^2$ (df = 15)	1,470 <sup>***</sup>	671 <sup>***</sup>	1,214 <sup>***</sup>	1,575 <sup>***</sup>
Deviance	15,421	7,008	15,976	25,098
AIC	15,453	7,040	16,008	25,130

Note: <sup>\*\*\*</sup> $p < 0.001$ ; <sup>\*\*</sup> $p < 0.01$ ; <sup>\*</sup> $p < 0.05$ ;  $\cdot$  $p < 0.1$ ; Coeff. is coefficient; s.e. is standard error; Exp. is exposure; Betw. is betweenness; Sign. is signalised; Unsig. is unsignalised.