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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

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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

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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 Commision, 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[1] (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	%
Separated bicycle tracks								
Separated bicycle tracks	577	33.9	263	24.8	489	30.3	341	27.6
On-street cycling facilities								
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
Total	*1,703*	*100.0*	*1,059*	*100.0*	*1,614*	*100.0*	*1,237*	*100.0*

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

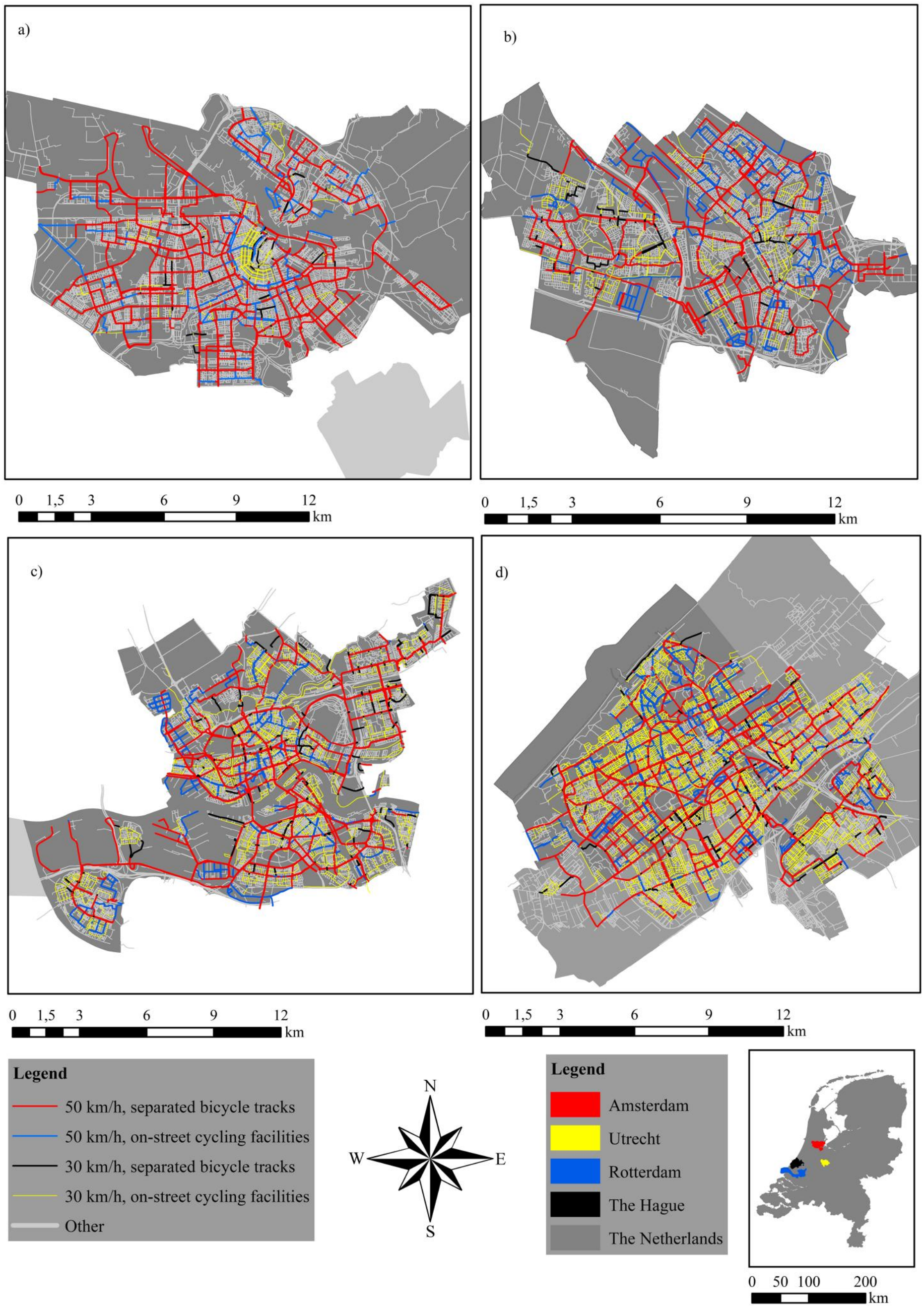

Figure 2. The analysed cycling network of (a) Amsterdam, (b) Utrecht, (c) Rotterdam, and (d) The Hague.

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
Exposure data	
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)
Infrastructural data	
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)
Destinations	
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
Cycling infrastructure												
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
Destinations within 150 m												
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. 7×24) 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
Total	*4,598*	*32*	*1*	*4,665*	*3,059,655*

(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)	**−8.93** (0.07)***	**−7.00** (0.20)***	**−6.63** (0.17)***
Exposure			
Exp. to cyclists (log)	**0.47** (0.02)***	**0.65** (0.03)***	**0.61** (0.03)***
Exp. to motorised vehicles (log)	**0.28** (0.01)***	**0.13** (0.02)***	**0.11** (0.02)***
Temporal (ref = morning/day 06:00-18:00)			
Evening/night 18:00-06:00	**−0.50** (0.03)***	-	-
Network structure			
Betw. centrality (normalised)	**4.72** (0.84)***	**6.52** (1.40)***	**5.76** (1.17)***
Sign. intersection density (scaled)	**0.31** (0.02)***	**0.30** (0.03)***	**0.32** (0.03)***
Roundabout density (scaled)	**0.21** (0.02)***	**0.22** (0.03)***	**0.22** (0.02)***
Unsig. intersection density (scaled)	**0.39** (0.02)***	**0.41** (0.03)***	**0.39** (0.03)***
Grade-separated road sections	0.00 (0.05)	0.01 (0.08)	0.01 (0.07)
Cycling infrastructure (ref = 30 km/h, on-street cycling facilities)			
50 km/h, separated bicycle tracks	**−0.46** (0.05)***	**−0.19** (0.07)**	**−0.10** (0.06)·
50 km/h, on-street cycling facilities	0.04 (0.05)	**0.24** (0.07)**	**0.25** (0.06)***
30 km/h, separated bicycle tracks	**0.18** (0.07)*	0.12 (0.11)	**0.22** (0.10)*
Destinations within 150 metres			
Commercial facilities	**0.60** (0.03)***	**0.55** (0.04)***	**0.56** (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)	**0.14** (0.05)**	0.05 (0.05)
Unobserved city-specific factors (ref = Rotterdam)			
Amsterdam	**1.20** (0.05)***	**1.41** (0.08)***	**1.32** (0.07)***
Utrecht	**0.66** (0.06)***	**0.95** (0.09)***	**0.82** (0.08)***
The Hague	**0.97** (0.05)***	**1.25** (0.08)***	**1.17** (0.07)***
Num. obs.	3,063,816	18,237	18,237
Log Likelihood	−31,819	−7,211	−10,055
Likelihood ratio χ^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: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $\cdot p < 0.1$; 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

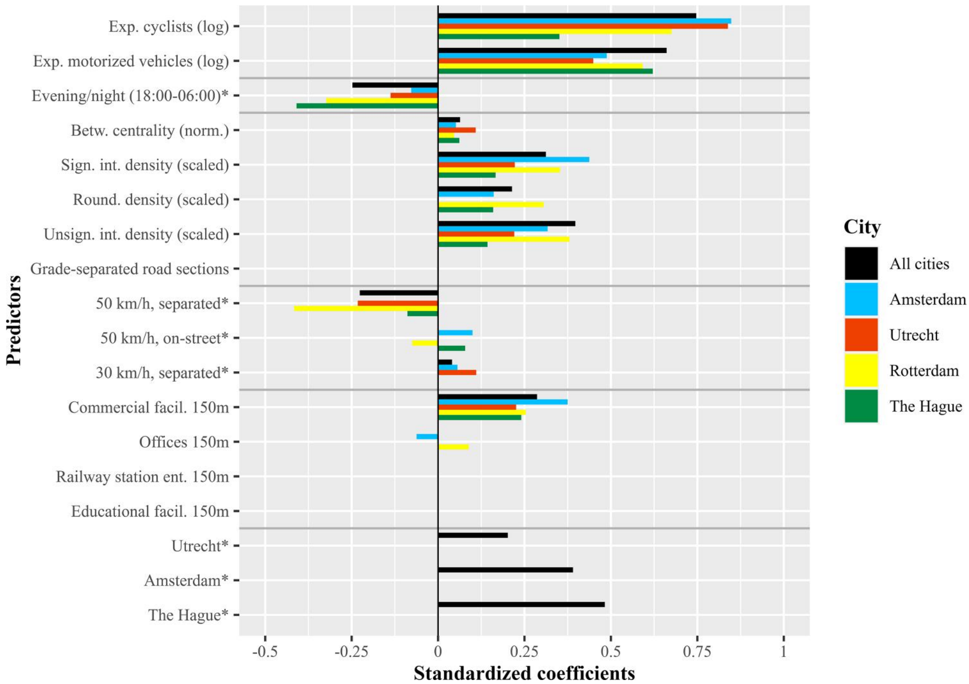

Figure 3. Standardised coefficient estimates of the five logistic regression models (dependent variable is presence of a crash (0 or 1) at a road section at a given hour).

*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 hotspots 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.

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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.

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References

Adminaité-Fodor, D., & Jost, G. (2020). *How safe is walking and cycling in Europe?* European Transport Safety Council. https://etsc.eu/wp-content/uploads/PIN-Flash-38_FINAL.pdf

Aldred, R., Goodman, A., Gulliver, J., & Woodcock, J. (2018). Cycling injury risk in London: A case-control study exploring the impact of cycle volumes, motor vehicle volumes, and road characteristics including speed limits. *Accident, Analysis & Prevention*, *117*, 75–84. doi:10.1016/j.aap.2018.03.003

Bernardi, S., La Paix Puello, L., & Geurs, K. T. (2018). Modelling route choice of Dutch cyclists using smartphone data. *Journal of Transport and Land Use*, *11*(1), 883–900. https://www.jstor.org/stable/26622435 doi:10.5198/jtlu.2018.1143

Buehler, R., & Pucher, J. (2021). COVID-19 impacts on cycling, 2019–2020. *Transport Reviews*, *41*(4), 393–400. doi:10.1080/01441647.2021.1914900

Cui, Y., Mishra, S., & Welch, T. F. (2014). Land use effects on bicycle ridership: A framework for state planning agencies. *Journal of Transport Geography*, *41*, 220–228. doi:10.1016/j.jtrangeo.2014.10.004

Cycling Intelligence. (2021). *Nationale Fietstelweek 2015, 2016, 2017 [National Bicycle Counting Week 2015, 2016, 2017]*. Breda University of Applied Science. http://opendata.cyclingintelligence.eu/

Derriks, H. M., & Mak, P. M. (2007). *IRTAD special report: Underreporting of road traffic casualties*. IRTAD International Traffic Safety Data and Analysis Group.

DiGioia, J., Watkins, K. E., Xu, Y., Rodgers, M., & Guensler, R. (2017). Safety impacts of bicycle infrastructure: A critical review. *Journal of Safety Research*, *61*, 105–119. doi:10.1016/j.jsr.2017.02.015

Dozza, M. (2017). Crash risk: How cycling flow can help explain crash data. *Accident; Analysis and Prevention*, *105*, 21–29. doi:10.1016/j.aap.2016.04.033

DUO. (2022). *Onderwijslocaties [Education locations]*. https://www.arcgis.com/home/item.html?id=4bb5ba9f3f664db1812cd4898907d4f7

Dutch Cyclists' Union. (2020). *Fietsrouteplanner [Bicycle Route Planner]*. https://en.routeplanner.fietsersbond.nl/

Elvik, R. (2006). Laws of accident causation. *Accident, Analysis & Prevention*, *38*(4), 742–747. doi:10.1016/j.aap.2006.01.005

European Commision. (2022). *Annual statistical report on road safety in the EU, 2021*. European Road Safety Observatory. European Commission. Directorate General for Transport. https://road-safety.transport.ec.europa.eu/system/files/2022-05/ERSO_annual_report_20220509.pdf

Faghih-Imani, A., Eluru, N., El-Geneidy, A. M., Rabbat, M., & Haq, U. (2014). How land-use and urban form impact bicycle flows: Evidence from the bicycle-sharing system (BIXI) in Montreal. *Journal of Transport Geography*, *41*, 306–314. doi:10.1016/j.jtrangeo.2014.01.013

Ferster, C., Nelson, T., Laberee, K., & Winters, M. (2021). Mapping bicycling exposure and safety risk using Strava Metro. *Applied Geography*, *127*, 102388. doi:10.1016/j.apgeog.2021.102388

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks*, *1*(3), 215–239. doi:10.1016/0378-8733(78)90021-7

Gil, J. (2017). Street network analysis "edge effects": Examining the sensitivity of centrality measures to boundary conditions. *Environment and Planning B: Urban Analytics and City Science*, *44*(5), 819–836. doi:10.1177/0265813516650678

Givoni, M., & Rietveld, P. (2007). The access journey to the railway station and its role in passengers' satisfaction with rail travel. *Transport Policy*, *14*(5), 357–365. doi:10.1016/j.tranpol.2007.04.004

Gleave, S. D. (2012). *Cycle route choice*. Transport for London. https://content.tfl.gov.uk/understanding-cycle-route-choice.pdf

Guo, Y., Li, Z., Wu, Y., & Xu, C. (2018). Exploring unobserved heterogeneity in bicyclists' red-light running behaviors at different crossing facilities. *Accident; Analysis and Prevention*, *115*, 118–127. doi:10.1016/j.aap.2018.03.006

Guo, Y., Osama, A., & Sayed, T. (2018). A cross-comparison of different techniques for modeling macro-level cyclist crashes. *Accident, Analysis & Prevention*, *113*, 38–46. doi:10.1016/j.aap.2018.01.015

Harms, L., Bertolini, L., & Te Brömmelstroet, M. (2014). Spatial and social variations in cycling patterns in a mature cycling country exploring differences and trends. *Journal of Transport & Health*, *1*(4), 232–242. doi:10.1016/j.jth.2014.09.012

Jonkeren, O., Wust, H., & de Haas, M. (2019). *Mobiliteit in stedelijk Nederland [Mobility in Dutch urban areas]*. KiM Netherlands Institute for Transport Policy Analysis.

Kadaster. (2022). *Basisregistratie Adressen en Gebouwen (BAG) [register for all addresses and buidling in the Netherlands]*. https://bagviewer.kadaster.nl/lvbag/bag-viewer/index.html#?geometry.x=160000&geometry.y=455000&zoomlevel=0

Kamel, M. B., & Sayed, T. (2021). The impact of bike network indicators on bike kilometers traveled and bike safety: A network theory approach. *Environment and Planning B: Urban Analytics and City Science*, *48*(7), 2055–2072. doi:10.1177/2399808320964469

Kaplan, S., & Prato, C. G. (2015). A spatial analysis of land use and network effects on frequency and severity of cyclist–motorist crashes in the Copenhagen region. *Traffic Injury Prevention*, *16*(7), 724–731. doi:10.1080/15389588.2014.1003818

Kim, K., Pant, P., & Yamashita, E. (2010). Accidents and accessibility: Measuring influences of demographic and land use variables in Honolulu, Hawaii. *Transportation Research Record: Journal of the Transportation Research Board*, *2147*(1), 9–17. doi:10.3141/2147-02

Loidl, M., Traun, C., & Wallentin, G. (2016). Spatial patterns and temporal dynamics of urban bicycle crashes—A case study from Salzburg (Austria). *Journal of Transport Geography*, *52*, 38–50. doi:10.1016/j.jtrangeo.2016.02.008

Lovelace, R., Roberts, H., & Kellar, I. (2016). Who, where, when: The demographic and geographic distribution of bicycle crashes in West Yorkshire. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 277–293. doi:10.1016/j.trf.2015.02.010

Lücken, L., & Wagner, P. (2020). On the relation between bicycle volumes and individual risks for bicyclists in Berlin. *Journal of Transportation Safety & Security*, *12*(1), 210–223. doi:10.1080/19439962.2019.1597003

Merlin, L. A., Guerra, E., & Dumbaugh, E. (2020). Crash risk, crash exposure, and the built environment: A conceptual review. *Accident; Analysis and Prevention*, *134*, 105244. doi:10.1016/j.aap.2019.07.020

Metropolitan Region Rotterdam The Hague. (2021). *V-MRDH 2.10*.

Mittlböck, M., & Heinzl, H. (2001). A note on R2 measures for Poisson and logistic regression models when both models are applicable. *Journal of Clinical Epidemiology*, *54*(1), 99–103. doi:10.1016/S0895-4356(00)00292-4

Mukoko, K. K., & Pulugurtha, S. S. (2020). Examining the influence of network, land use, and demographic characteristics to estimate the number of bicycle-vehicle crashes on urban roads. *IATSS Research*, *44*(1), 8–16. doi:10.1016/j.iatssr.2019.04.001

Mulvaney, C. A., Smith, S., Watson, M. C., Parkin, J., Coupland, C., Miller, P., Kendrick, D., & McClintock, H. (2015). Cycling infrastructure for reducing cycling injuries in cyclists. *The Cochrane Database of Systematic Reviews*, *2015*(12), CD010415. doi:10.1002/14651858.CD010415.pub2

Municipality of Amsterdam. (2016). *Telplan Amsterdam 2016 [Count plan Amsterdam 2016]*.

Municipality of Amsterdam. (2022). *Traffic prognoses Amsterdam 4.1*. https://maps.amsterdam.nl/verkeersprognoses/?LANG=en

Municipality of The Hague (2019). *Fietstelling rapporten [Bicycle count reports]*.

Municipality of Utrecht. (2018). *VRU 3.4*

Municipality of Utrecht. (2020). *Utrecht Fietstellingen 2015-2019 [Bicycle counts Utrecht 2015-2019]*.

Nashad, T., Yasmin, S., Eluru, N., Lee, J., & Abdel-Aty, M. A. (2016). Joint modeling of pedestrian and bicycle crashes: Copula-based approach. *Transportation Research Record: Journal of the Transportation Research Board*, *2601*(1), 119–127. doi:10.3141/2601-14

NDW Dexter. (2022). *Dexter Data Exploration + Exporter*. National Road Traffic Data Portal (NDW). https://dexter.ndwcloud.nu/

Nieminen, P., Lehtiniemi, H., Vähäkangas, K., Huusko, A., & Rautio, A. (2013). Standardised regression coefficient as an effect size index in summarising findings in epidemiological studies. *Epidemiology Biostatistics and Public Health*, *10*(4), 1–15. doi:10.2427/8854

Osama, A., & Sayed, T. (2016). Evaluating the impact of bike network indicators on cyclist safety using macro-level collision prediction models. *Accident, Analysis & Prevention*, *97*, 28–37. doi:10.1016/j.aap.2016.08.010

Porta, S., Strano, E., Iacoviello, V., Messora, R., Latora, V., Cardillo, A., Wang, F., & Scellato, S. (2009). Street centrality and densities of retail and services in Bologna, Italy. *Environment and Planning B: Planning and Design*, *36*(3), 450–465. doi:10.1068/b34098

Prato, C. G., Kaplan, S., Rasmussen, T. K., & Hels, T. (2016). Infrastructure and spatial effects on the frequency of cyclist-motorist collisions in the Copenhagen Region. *Journal of Transportation Safety & Security*, *8*(4), 346–360. doi:10.1080/19439962.2015.1055414

Province of North-Holland. (2022). *Portaal Kaart en Data [Maps and data portal]*. Provincie Noord-Holland. https://geoapps.noord-holland.nl/kaartenportaal/apps/MapSeries/index.html?appid=e85fc52939f240ba9ef5164b5e203fb2&entry=2

Province of South-Holland. (2022). *Open-dataportaal [Open data portal]*. Province of South Holland. https://opendata.zuid-holland.nl/geonetwork/srv/eng/catalog.search#/home

Province of Utrecht. (2018). *Geo-Point Utrecht*. Province of Utrecht. https://geo-point.provincie-utrecht.nl/

Pulugurtha, S. S., & Thakur, V. (2015). Evaluating the effectiveness of on-street bicycle lane and assessing risk to bicyclists in Charlotte, North Carolina. *Accident; Analysis and Prevention*, *76*, 34–41. doi:10.1016/j.aap.2014.12.020

Rijkswaterstaat. (2019). *Nationaal Wegenbestand (NWB)*.

Rijkswaterstaat. (2020a). *Bestand geRegistreerde Ongevallen Nederland [Database of registered crashes in the Netherlands]*. https://data.overheid.nl/dataset/a516ffaf-fbcc-44bc-88cb-fca799c5cd29

Rijkswaterstaat. (2020b). *Wegkenmerken +/Speed [Road characteristics +/Speed]*. https://data.overheid.nl/dataset/492fd275-0ef4-46c0-8642-5e7fb3e041af

Salmon, P. M., Naughton, M., Hulme, A., & McLean, S. (2022). Bicycle crash contributory factors: A systematic review. *Safety Science*, *145*, 105511. doi:10.1016/j.ssci.2021.105511

Schepers, P. (2021). *Ruimtelijke inrichting en verkeersveiligheid; Verkenning voor stedelijke gebieden met een accent op kwetsbare verkeersdeelnemers [Spatial planning and road safety; Exploration for urban areas with a focus on vulnerable road users]*. SWOV. https://swov.nl/nl/publicatie/ruimtelijke-inrichting-en-verkeersveiligheid

Schepers, P., Helbich, M., Hagenzieker, M., de Geus, B., Dozza, M., Agerholm, N., Niska, A., Airaksinen, N., Papon, F., Gerike, R., Bjørnskau, T., & Aldred, R. (2021). The development of cycling in European countries since 1990. *European Journal of Transport and Infrastructure Research*, *21*(2), 41–70. doi:10.18757/ejtir.2021.21.2.5411

Sevtsuk, A., Mekonnen, M., & Kalvo, R. (2016). *Urban Network Analyst* (1.01 1.01) [Toolbox for ArcGIS]. City Form Lab, MIT. http://cityform.mit.edu/projects/urban-network-analysis.html

Statistics Netherlands (CBS). (2022). *Inwoners per gemeente [Inhabitants per municipality]*. https://www.cbs.nl/nl-nl/visualisaties/dashboard-bevolking/regionaal/inwoners

SWOV. (2018). *Sustainable Safety 3rd edition—The advanced vision for 2018-2030. Principles for design and organization of a casualty-free road traffic system*. SWOV. https://swov.nl/nl/publicatie/sustainable-safety-3rd-edition-advanced-vision-2018-2030

Thomas, B., & De Robertis, M. (2013). The safety of urban cycle tracks: A review of the literature. *Accident, Analysis & Prevention*, *52*, 219–227. doi:10.1016/j.aap.2012.12.017

Twisk, D. A. M., Vlakveld, W. P., Dijkstra, A., Reurings, M., & Wijnen, W. (2013). *From bicycle crashes to measures*. SWOV. https://swov.nl/nl/publicatie/bicycle-crashes-measures

Uijtdewilligen, T., Ulak, M. B., Wijlhuizen, G. J., Bijleveld, F., Dijkstra, A., & Geurs, K. T. (2022). How does hourly variation in exposure to cyclists and motorised vehicles affect cyclist safety? A case study from a Dutch cycling capital. *Safety Science*, *152*, 105740. doi: 10.1016/j.ssci.2022.105740

Ulak, M. B., Ozguven, E. E., Vanli, O. A., Dulebenets, M. A., & Spainhour, L. (2018). Multivariate random parameter Tobit modeling of crashes involving aging drivers, passengers, bicyclists, and pedestrians: Spatiotemporal variations. *Accident, Analysis & Prevention*, *121*, 1–13. doi:10.1016/j.aap.2018.08.031

van Petegem, J. W. H., Schepers, P., & Wijlhuizen, G. J. (2021). The safety of physically separated cycle tracks compared to marked cycle lanes and mixed traffic conditions in Amsterdam. *European Journal of Transport and Infrastructure Research*, *21*(3), 19–37. doi:10.18757/ejtir.2021.21.3.5283

Vandenbulcke, G., Thomas, I., & Int Panis, L. (2014). Predicting cycling accident risk in Brussels: A spatial case-control approach. *Accident, Analysis & Prevention*, *62*, 341–357. doi:10.1016/j.aap.2013.07.001

Wang, H., Chang, S. K. J., De Backer, H., Lauwers, D., & De Maeyer, P. (2019). Integrating spatial and temporal approaches for explaining bicycle crashes in high-risk areas in Antwerp (Belgium). *Sustainability*, *11*(13), 3746. doi:10.3390/su11133746

Wang, H., De Backer, H., Lauwers, D., & Chang, S. K. J. (2019). A spatio-temporal mapping to assess bicycle collision risks on high-risk areas (Bridges)—A case study from Taipei (Taiwan). *Journal of Transport Geography*, *75*, 94–109. doi:10.1016/j.jtrangeo.2019.01.014

Washington, S. P., Karlaftis, M. G., & Mannering, F. L. (2011). *Statistical and econometric methods for transportation data analysis* (S. P. Washington, M. G. Karlaftis, & F. L. Mannering (Eds.)). Chapman & Hall/CRC.

Wegman, F., Zhang, F., & Dijkstra, A. (2012). How to make more cycling good for road safety? *Accident, Analysis & Prevention*, *44*(1), 19–29. doi:10.1016/j.aap.2010.11.010

Wei, F., & Lovegrove, G. (2013). An empirical tool to evaluate the safety of cyclists: Community based, macro-level collision prediction models using negative binomial regression. *Accident, Analysis & Prevention*, *61*, 129–137. doi:10.1016/j.aap.2012.05.018

Welleman, A. G., Dijkstra, A. (1988). *Veiligheidsaspecten van stedelijke fietspaden [The safety of urban bicycle tracks]*. SWOV. https://swov.nl/nl/publicatie/veiligheidsaspecten-van-stedelijke-fietspaden

Williams, T., Page, S., & Doscher, C. (2018). Spatial characteristics of bicycle–motor vehicle crashes in Christchurch, New Zealand: A case-control approach. *Journal of Transport and Land Use*, *11*(1), 849–864. doi:10.5198/jtlu.2018.1147

Zhang, Y., Bigham, J., Ragland, D., & Chen, X. (2015). Investigating the associations between road network structure and non-motorist accidents. *Journal of Transport Geography*, *42*, 34–47. doi:10.1016/j.jtrangeo.2014.10.010

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
Exposure	*hours*					*vol*km*	*hours*					*vol*km*	*hours*					*vol*km*	*hours*					*vol*km*
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	25,999624	1,656,648	16.08	47.16	0.00	2,301	26,638,850
Temporal						*hours*						*hours*						*hours*						*hours*
Daytime 06:00-18:00	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 18:00-06:00	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
Network structure	*road sections*						*road sections*						*road sections*						*road sections*					
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
Cycling infrastructure						*km (prop.)*						*km (prop.)*						*km (prop.)*						*km (prop.)*
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						*km (prop.)*						*km (prop.)*						*km (prop.)*						*km (prop.)*
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 *Coeff. (s.e.)*	Utrecht *Coeff. (s.e.)*	Rotterdam *Coeff. (s.e.)*	The Hague *Coeff. (s.e.)*
(Intercept)	**−8.23** (0.13)***	**−8.32** (0.16)***	**−8.65** (0.13)***	**−7.69** (0.07)***
Exposure				
Exp. to cyclists (log)	**0.52** (0.03)***	**0.55** (0.04)***	**0.47** (0.03)***	**0.30** (0.03)***
Exp. to motorised vehicles (log)	**0.26** (0.03)***	**0.19** (0.03)***	**0.30** (0.03)***	**0.27** (0.02)***
Temporal				
Evening/night 18:00-06:00	**−0.16** (0.06)*	**−0.27** (0.10)**	**−0.65** (0.07)***	**−0.82** (0.06)***
Network structure				
Betw. centrality (normalised)	**3.87** (1.83)*	**6.05** (1.86)**	**3.17** (1.69)·	**5.30** (1.49)***
Sign. intersection density (scaled)	**0.43** (0.05)***	**0.22** (0.08)**	**0.35** (0.04)***	**0.17** (0.03)***
Roundabout density (scaled)	**0.16** (0.07)*	0.08 (0.12)	**0.30** (0.05)***	**0.16** (0.02)***
Unsig. intersection density (scaled)	**0.31** (0.05)***	**0.21** (0.08)**	**0.37** (0.05)***	**0.14** (0.02)***
Grade-separated road sections	0.03 (0.06)	0.06 (0.15)	−0.05 (0.10)	−0.10 (0.13)
Cycling infrastructure (ref = 30 km/h, on-street cycling facilities				
50 km/h, separated bicycle tracks	−0.17 (0.11)	**−0.47** (0.13)***	**−0.83** (0.09)***	**−0.19** (0.08)*
50 km/h, on-street cycling facilities	**0.29** (0.12)*	−0.09 (0.16)	**−0.22** (0.10)*	**0.22** (0.08)**
30 km/h, separated bicycle tracks	**0.41** (0.18)*	**0.42** (0.17)*	−0.16 (0.14)	0.11 (0.14)
Destinations within 150 metres				
Commercial facilities	**0.75** (0.07)***	**0.49** (0.10)***	**0.52** (0.06)***	**0.52** (0.05)***
Office buildings	**−0.17** (0.09)·	0.12 (0.10)	**0.25** (0.07)***	−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 χ^2 (df = 15)	1,470***	671***	1,214***	1,575***
Deviance	15,421	7,008	15,976	25,098
AIC	15,453	7,040	16,008	25,130

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