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# Speed variables on Rijkswaterstaat N-roads and their relationship with crash likelihood and crash severity

BSc thesis

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# Preface

This thesis is the culmination of my years in the Civil Engineering bachelor and describes the relationship between several speed variables and accident risk on a specific single-lane/carriageway subset of Rijkwaterstaat managed N-roads. During my research, I discovered how much I enjoyed these kinds of traffic analyses and that I would like to continue learning about this and related subjects.

This assignment was carried out externally at Rijkswaterstaat between April and August of 2023, to offer Rijkswaterstaat insight into measures that can be effective in improving traffic safety on their network.

Firstly, I would like to thank my external supervisor, Paul Schepers, for granting me the opportunity to carry out my research at Rijkswaterstaat and giving me insight into how traffic management is carried in day-to-day life. I would also like to thank him for his continued support and feedback from the preparation phase through to the finalizing writing phase of this research.

Secondly, I would also like to thank my university supervisor, Baran Ulak, for his assistance in finding an assignment and guidance throughout this research. In addition, I would also like to thank Mehrnaz Asadi for her guidance during the analysis and writing phases.

Thirdly, I would like to thank Werner van Loo of the NDW for gathering and sharing all speed data, which considerably helped the analysis for the speed variables.

Finally, I would like to thank my friends and family for proving me with continued feedback on all my drafts, which has greatly helped finalizing this thesis, and supporting me throughout my bachelors in general.

Tzora Tacx,

Enschede, August 2023

# Summary

Road safety is an important aspect of traffic management. Road safety is most often measured in fatal crashes. For governments and other road managers to determine how to decrease the number of fatal crashes on their roads, it is important to determine what factors influence crash likelihood and crash severity. This research aims to answer that question for several speed variables on roads managed by Rijkswaterstaat, specifically N-roads without physical separation (1x2 connected lanes) and with physical separation (2x1 separated carriageways).

In addition to the speed variables (S85, deviation from the speed limit, standard deviation of speeds during two off-peak and two peak time periods, coefficient of variation of speeds on one road section), through literature review, several traffic and road characteristic variables (vehicle kilometres, freight percentage, lane width, shoulder width, verge design, median width, horizontal alignment, merging lane presence, junction density) were found to have a relationship with the dependent variables crash likelihood and crash severity. Furthermore, the interaction effects between speed and vehicle kilometres, speed and junction density, speed and verge design, speed and shoulder width, speed and horizontal alignment, and speed and lane width, were found to have a relationship with crash likelihood and crash severity.

The statistical analysis showed that the standard deviation of speeds during the evening peak hours and the S85 of speeds are significantly correlated with crash likelihood, in addition to a median width of 1.0 through 2.0 metres and vehicle kilometres. When accounting for interaction effects, an additional relevant result is the statistically significant relationship between the interaction effect of the S85 and verge design and crash likelihood. However, no statistically significant relationships between speed variables and crash severity were found. The only statistically significant relationship was found between junction density and crash severity. The lack of results for crash severity is ascribed to data limitations. These data limitations warrant further research using other sources for crash data, in addition to further research being needed which takes a longer data period into account, looks at different ways to structure the data, researches the relationship between speed deviations and time of day, and verifies the relationships in this study with other data.

Finally, based on the results, practical recommendations to which could decrease crash likelihood and crash severity include reducing speed deviations, redesigning verges, turning at-grade junctions into separated junctions, and avoiding narrow medians.

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# 1. Introduction

This thesis aims to give insights into the safety performance of N-roads, part of the Dutch national roadwork, managed by Rijkswaterstaat For this purpose, this thesis investigated the relationship of certain speed variables with crash risk on N-roads. Specifically, N-roads with and without physical opposite traffic separation and with only one lane in each travel direction.

Investigating road safety is a continuing concern within traffic management. The most common metric for the road safety performance is the number of fatal crashes. The Netherlands formulated the goal of zero traffic fatalities within the country in 2050. In addition, the Netherlands is working on reaching the EU and UN goals of halving the number of traffic fatalities in 2030 compared to 2020 (Geurts, 2021). An important step in reaching this goal is insight into what risk factors play a role in (fatal) traffic crashes (SPV 2030, 2018, p. 23).

Crashes have a high societal impact, both in terms of immaterial and material costs. In 2022 in the Netherlands, 737 people lost their life due to traffic crashes (CBS, 2023). By the latest estimate of the SWOV (Institute for Road Safety Research), the number of serious road injuries amounted to 6,800 in 2021, with a severity at the Maximum Abbreviated Injury Scale of 3 or higher (SWOV, 2022, p. 54).

Since 1950, the start of the registration period of crash fatalities in the Netherlands, the number of crash fatalities in the Netherlands increased until 1972 and decreased steadily from 1973 onwards. However, this trend stagnated around 2013 and 2014 (SWOV, 2023, pp. 3, 10). The number of crash fatalities are following a rising trend again, with the number of crash fatalities in 2022 being the highest since 2008 (SWOV, 2023, p. 11). The crash fatalities in the Netherlands from 1950 through 2022 can be found in figure 1.

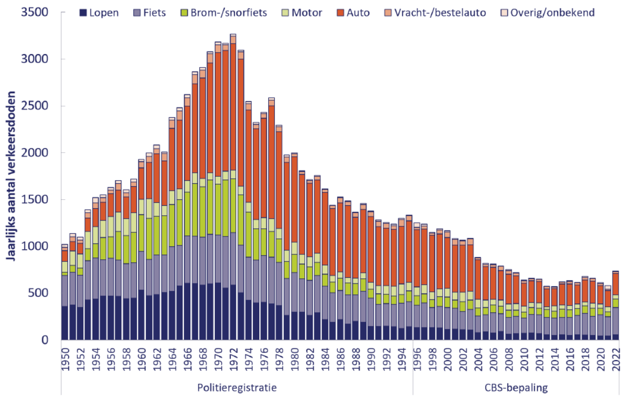


*Figure 1: Pattern of crash fatalities (1950-2022) (SWOV, 2023, p. 11)*

Proposed measures, like refurbishing 80 km/h N-roads to comply with the highest safety standards, will have a positive effect on the number of crash fatalities (SWOV, 2022, p. 39), however, the studies on the impact of these measures don't investigate the relationship between the original road characteristics and crash risk.

The Netherlands had 141,242 kilometres of paved road in 2021 (CBS, 2023). Four main road authorities manage these roads, namely: Rijkswaterstaat, provinces, municipalities and the water boards. In 2021, Rijkswaterstaat managed around 5,534 km of road, provinces managed around 7,905 km of road and municipalities and water boards together managed around 127,804 km of road (CBS, 2023).

About a third of the roads Rijkswaterstaat manages are N-roads, with motorways (A-roads) making up the rest. N-roads consist of 'autowegen' (speed limit of 100 km/h) and distributor roads, mostly with speed limits of 80 km/h. The N-roads managed by Rijkswaterstaat are shown in figure 2.


*Figure 2: RWS managed A-roads (red) and N-roads (green)*

N-roads are an area of concern because provincial N-roads are extremely unsafe, accounting for one in five fatal crashes (RTL Nieuws, 2018). N-roads managed by Rijkswaterstaat, especially the N36 and N50, can also be dangerous. In order to address the need for safer infrastructure, government investments into measures like physical separation barriers, better verge design, and turning at-grade intersections into grade separated intersections have been proposed (Harbers, 2022, p. 1). Around €200 million will be invested into renewing sixteen different RWS managed N-roads (Rijksoverheid, 2022).

This study focused on these Rijkswaterstaat N-roads, with the goal of providing measures to improve road safety. The remaining part of the paper proceeds as follows: a problem statement and research questions, followed by a literature review. Then, the data is described, in addition to the study area. Following that, the methodology is detailed, and summary statistics are given. Finally, the results are shown and discussed, finishing with a conclusion.

## 1.1. Problem statement

In general, N-roads with no physical separation between lanes in opposite direction are the least safe roads of those managed by RWS (Visser, 2021, p. 2). The safest solution is physical separation by barriers (Kennisnetwerk SPV, sd) or a sufficiently wide median strip. This solution is being implemented in some areas, but not cannot be done everywhere, due to financial, space, environmental, or societal constraints.

Some temporary solutions that are implemented include lowering the speed limit and installing temporary opposite traffic separation barriers on a few of the most dangerous roads. For example. the speed limit has temporarily been reduced on the N50 (Rijksoverheid, 2022). Using temporary speed limit reductions brings up an interesting question. There has been a lack of research regarding the link between speed and crash risk on single lane RWS N-roads. While previous research has shown that lower driving speeds leads to lower chances of fatal crashes (SWOV, 2021, p. 6), these do not take into account the structural properties of N-roads. Hence, the current research aims to investigate the link between speed and crash risks on Rijkswaterstaat managed N- roads with and without physical opposite traffic separation, specifically with one lane in each travel direction.

## 1.2. Research questions

Based on this objective, the main research question in this thesis is: How are speed and speed variation related to the crash risk on RWS managed N-roads without physical separation (1x2 connected lanes) and with physical separation (2x1 separated carriageways)? This question was further explored with the following sub questions:

1) What is the relationship of the chosen speed variables with crash likelihood?
2) What is the relationship of the chosen speed variables with crash severity?

# 2. Literature research

This section gives a brief literature review on effective factors including the speed variables, road design factors, and traffic characteristics on crash risk.

## 2.1. Factors affecting crash risk

In order to reduce the number of crashes and attempt to reach the goals, it is important to determine what factors influence crash risk and crash severity. A multitude of factors have an impact on the frequency and severity of crashes in general. Research recognizes the impact of traffic volume (Høye & Hesjevoll, 2020, p. 2), speed (ITF, 2018, p. 7), vehicle design (Huang, Siddiqui, & Abdel-Aty, 2011, p. 1368), speed variation (Choudhary, Imprialou, Velaga, & Choudhary, 2018, p. 217), road geometry (Wang, Quddus, & Ison, 2013, pp. 269-270), verge design (Kloeden, McLean, Baldock, & Cockington, 1999, p. 61), and median characteristics (Tarko, Vilwock, & Blond, 2008, p. 36) on crash likelihood and crash severity. Most crashes take place between cars. In addition, users of lighter transport modes are more likely to be seriously injured if they are involved in a crash (e.g. crashes between cars and lorries) because they have more energy to absorb than occupants of heavy vehicles and are less well protected by their vehicle (Schoon & Bos, 2002, p. 36) (Tolouei, Maher, & Titheridge, 2012, pp. 155-156) (Huang, Siddiqui, & Abdel-Aty, 2011, p. 1368). Vehicle design is, however, out of scope for this research.

### 2.1.1. Exposure: vehicle kilometres

Traffic volume is a well-established contributor to crash frequency (Høye & Hesjevoll, 2020, p. 3). Multiple studies have found that an increase in exposure, measured in vehicle kilometres, leads to an increase in crash frequency (Hakkert & Braimaister, 2002, p. 43) (Tros, 2022, p. 5).

### 2.1.2. Freight traffic percentage

Research has found a link between the ratio of truck traffic and the occurrence of crash risk hot spots (Wu, et al., 2023, p. 16), leading to inclusion of freight traffic percentage in this study. Several risk factors can be of influence. In the Netherlands, heavy traffic (maximum mass>3500 kg) has a maximum speed limit of 80 km/h everywhere (RVV, 1990) (except some busses, which can go 100 km/h (RVV, 1990)). This means that there is usually a continuous speed difference between regular cars, and busses and lorries. The lower speed may decrease crash risk, but this may be offset by a greater speed difference (SWOV, 2021, p. 7). In addition, when a lorry crashes with another vehicle, its occupant is 7.5 times more likely to die than they would if they'd crashed with a car (SWOV, 2020, p. 6). On the other hand, lorries have a lower risk of severe single-vehicle crashes.

### 2.1.3. General speed-crash relationship

The relationship between speed and crash risk and crash severity is well-researched. An increase in the individual speed of a vehicle leads to an increased crash risk (Aarts & van Schagen, 2006, p. 218). This relationship also holds for an increase in the average speed on a road (section) (Aarts & van Schagen, 2006, p. 220) (Gargoum & El-Basyouny, 2016, p. 38) (SWOV, 2021, p. 5). Another study finds that crash likelihoods increase proportionally with speed, until it stabilises and decreases, which could be due to the decrease of crash prone reactions after speed has reached a high value (Imprialou, Quddus, Pitfield, & Lord, 2016, p. 182)

In general, speed increases, either on an individual or a road level, lead to a higher crash rate on urban roads compared to rural roads (Aarts & van Schagen, 2006, pp. 218, 220).

Speed variation, deviation from the average speed, has been found to be correlated with crash likelihoods (Wang, Quddus, & Ison, 2013, p. 267), though this correlation is positive and negative in different research and statistically insignificant in others (Gargoum & El-Basyouny, 2016, p. 38). A more recent research report mentions that speed variance between vehicles at the same place and time and crash risk are correlated positively, though it does specify the variations in the numerical estimates (ITF, 2018, p. 22). Individual vehicles with a higher speed than the average road speed also have a higher crash risk (SWOV, 2021, p. 7).

Research indicates a positive relationship between impact speed and the risk of a serious injury when a crash occurs (Doecke, Dutschke, Baldock, & Kloeden, 2021, p. 3). Raising speed limits leads to a higher travel speed on roads and leads to higher fatality rates (Farmer, 2017, pp. 378-379).

#### 2.1.4. Road design elements

Road design elements have an impact on the frequency and severity of crashes. Narrow shoulder widths and smaller horizontal curve angles have been shown to increase crash frequency (Milton & Mannering, 1998, p. 403). In addition, sharp horizontal curves, larger horizontal curve radii, and smaller tangent lengths before curves have been shown to decrease crash frequency (Milton & Mannering, 1998, p. 403). Horizontal curves designed for speeds lower than those that are driven lead to an increase in most types of crashes (Shankar, Mannering, & Barfield, 1995, p. 382). Larger horizontal curve radii lead to more sideswipe collisions, and smaller horizontal curve radii in winding highway sections lead to less overturns (Shankar, Mannering, & Barfield, 1995, p. 383).

Median design, especially the installation of a physical barrier, has a definite effect on crash frequency and severity. Installing a median concrete barrier on a roadway led to a reduction in the number of head-on collisions but led to an increase in the total number of crashes (Tarko, Vilwock, & Blond, 2008, pp. 35-36) (Stamatiadis, Pigman, Sacksteder, Ruff, & Lord, 2009, p. 31). (Hadi, Aruldhas, Chow, & Wattleworth, 1995, pp. 175-176) found that an increase of median width led to a reduction in crashes, but that those benefits increased less as the median got wider. (Stamatiadis, Pigman, Sacksteder, Ruff, & Lord, 2009, p. 29) supports that conclusion, but only found significant results for multi-vehicle crashes.

Verge design impacts crash likelihood and severity, where research found that most crashes occurred in places where fatal hazards were less than 9 metres from the road, and concludes that a guard rail be an effective measure if hazards closer than 9 metres cannot be removed (Kloeden, McLean, Baldock, & Cockington, 1999, p. 55).

For N-roads specifically, it is clear that roads with a physical barrier separating travel directions have a lower likelihood of frontal crashes. Barriers are a guard rail or a physical separation of the lanes by sufficiently wide median. Historical data shows that roads with these types of barriers have a decreased risk of fatal crashes and an increased risk of non-fatal crashes compared to roads without a barrier. An overview of the types of risks and the roads with which they are associated can be found in table 1. The numbers are given for roads that have one lane for each direction, either without physical separation (1x2 connected lanes) and with physical separation (2x1 separated carriageways). The figure is calculated by dividing the number of victims by the amount of vehicle kilometres in billions.

*Table 1: Number of crashes per billion vehicle kilometres on RWS autowegen and other N-roads (based on (RWS, 2022, p. 146))*

| *Separation* | *Road type* | *Risk of fatal crash* | *Risk of crash with injury* |
|---|---|---|---|
| *No physical separation (1x2)* | Autoweg | 6.2 | 18.5 |
| | Other N-road | 3.9 | 33.6 |
| *Physical separation (2x1), crossable* | Autoweg | 2.8 | 32.2 |
| | Other N-road | 4.5 | 57.0 |
| *Physical separation (2x1), uncrossable* | Autoweg | 2.2 | 18.6 |
| | Other N-road | 0.0 | 51.2 |

Junctions are responsible for a high number of crashes (European Commission, sd). Research has shown that a higher density of junctions per kilometre leads to a higher crash frequency on rural single-lane carriageways (Taylor, Baruya, & Kennedy, The relationship between speed and accidents on rural single-carriageway roads, 2002, p. 19). In addition, a link between junction density and crash severity has also been found (SWOV, 2017, pp. 40-41).

## 2.2. Interaction effects

In addition to the individual effects of the factors detailed in section 0, interaction effects can also be present. Interaction effects between variables imply that the effect of one variable depends on the impact of another variable (Stevens, 2000, p. 1). There are multiple established relationships between driving speed and road design elements and traffic environment. Speed increases when verges are cleared and do not offer visual speed clues (SWOV, 2021, p. 14). When shoulders are narrow, drivers decrease their speed, and when shoulders are wider and guardrails are present, drivers increase their speed (Ben-Bassat & Shinar, 2011, pp. 2150-2151). When lanes are wider, drivers also increase their speed (SWOV, 2021, p. 14). In addition, as horizontal curves get sharper, driving speed decreases (Ben-Bassat & Shinar, 2011, p. 2150). Finally, speed also depends on traffic density (Lazda & Smirnovs, 2011, p. 393), as the speed decreases when congestion occurs (Wang, Quddus, & Ison, 2013, p. 266). This could be especially true for single lane roads, as there are no overtaking possibilities. This lends credibility to the inclusion of these interaction effects in the model, as it can be assumed that these relationships also hold true for the N-roads in the study.

## 2.3. Conceptual framework

Figure 3 below shows the relationships between the variables described in the sections above. The independent variables have a statistically significant relationship with the dependent variables, crash likelihood and crash severity. In addition, the interaction effects are a result of independent variables influencing each other and thus have a combined relationship with the dependent variables.

Moderator variables include variables like weather, lighting, driver characteristics, detailed road characteristics, and time-specific variables and characteristics. These variables could not be accounted for, due to the scope of the research and the available time but have been determined to influence the relationship between the independent/mediator variables and the dependent variables. For example, the relationship between speed and crash likelihood can be exacerbated by heavy rainfall, which can increase the risk for aquaplaning, or obscure the view for a driver. The higher speed and impaired vision can make a crash more likely or more severe because the driver does not notice a dangerous situation in time.

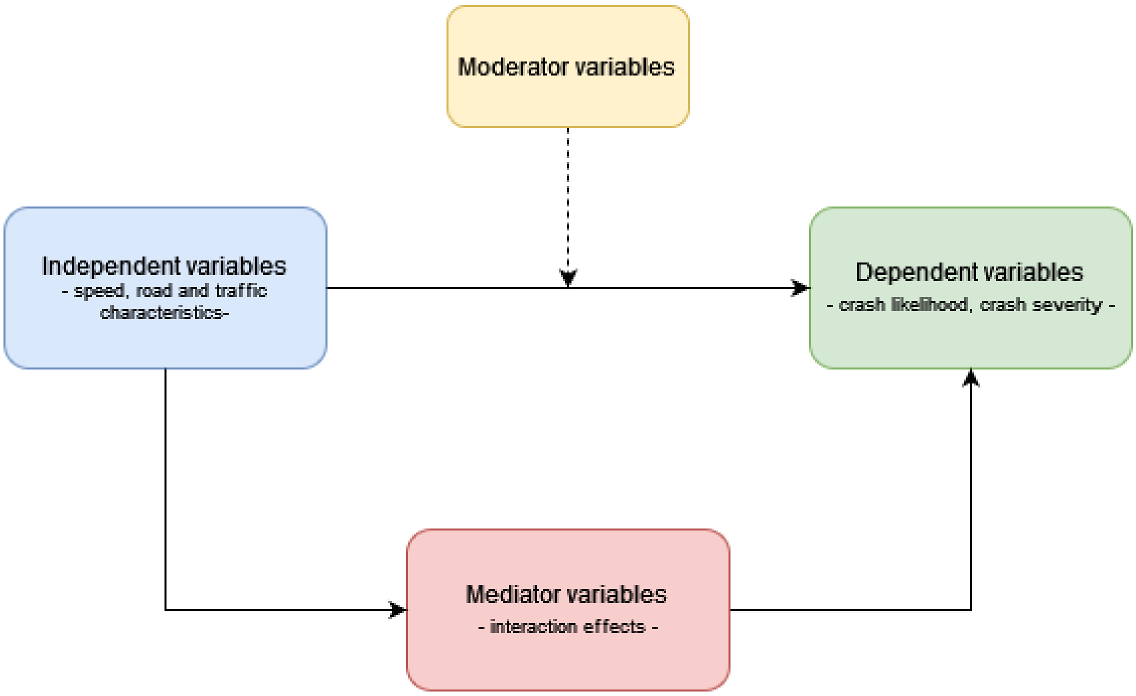


*Figure 3: General conceptual framework*

# 3. Data

Table 2 below gives an overview of what data was collected, where it came from, and which type of variable it was used for.

*Table 2: Data type, source, time period and variable type*

| *Type of data* | *Data source* | *Data period* | *Variable type* |
|---|---|---|---|
| *Crash counts and severity* | BRON (Bestand geRegistreerde Ongevallen in Nederland/File with Registered Crashes in the Netherlands) | 2018-2021 | Dependent |
| *Speed data (S85, FCD (Floating Car Data))* | NDW (Nationaal Dataportaal Wegverkeer/National Data Portal Road Traffic) | 2021 | Independent |
| *Road characteristics (length, lane count, etc.)* | NWB (Nationaal Wegenbestand/National Road Database) | 2021 | Independent |
| *Traffic characteristics* | INWEVA (INtensiteit WEgVAkken/Intensity Road Sections) | 2018-2021 | Independent |
| *Road design elements* | VIND (VeiligheidsINDicator/Safety Indicator) | 2021 | Independent |

The BRON database contains all crashes registered by police and Rijkswaterstaat (Rijkswaterstaat, sd). As police and Rijkswaterstaat are not present at every crash, there is a trend of underreporting (SWOV, 2023, p. 3) (Rijkswaterstaat, sd). Around 87% of all fatal crashes are registered in BRON, with single-vehicle crashes more likely to go unrecorded (SWOV, 2023, p. 3). Crashes resulting in less severe injuries are also less fully recorded. Still, because the BRON database includes information that is useful for road authorities, has specific information about the location and type of crash, and does not seem to have as large a problem for underreporting of crashes on the type of roads in this research, this database was used.

Road design characteristics and classifications through the VIND include numerical and categorical variables. The categorical variables are classified as follows: (good – green, safety management attention area – orange, inadequate –red, or no data/not applicable – blue). The categorial VIND indications are a score, based on the criteria that can be found in appendix 10.1.

The S85 is the speed that 85% of drivers do not exceed. The S85 is based on calculations on a sample of real-world data. In order for the NDW to accurately determine the S85, the speed limits of the road sections need to be correct. To determine whether the S85 was usable in this research, the maximum speed limits needed to be compared to a trustworthy database. In this case, this is the maximum speed limit database from the NWB. The S85 from 2018, 2019, and 2020 differed too much to be used. However, when comparing the S85 from 2021 with the NWB database, it appeared that though there was deviation in the two files, most of that deviation occurred outside of the study area. In addition, most of the deviation was due to differences in section ends and occurred mostly close to where the speed limit changed. This means that the S85 was fit for use in this research.

# 4. Study area

The study area encompasses all road sections that belong to a 2x1 and 1x2 N-road and are managed by Rijkswaterstaat. Road sections from the NWB database form the base location to which all variables are linked. These road sections do not have a fixed length, as the length is based on the distance between intersections/junction (excluding crosswalks where the road section is contiguous). The road between two intersections is one road section. Depending on the presence of physical separation of opposite driving directions, either two road sections or one road section is present between each intersection/junction. There are two road sections when lanes in opposite driving directions are physically separated (2x1) and there is one road section when there is no physical separation between the lanes (1x2).

First, the road sections were linked to their lane properties, omitting all sections which are less than 80% singe lane per direction, belonging to a 2x1 or 1x2 section. These road sections formed the basis for the routes for which FCD was gathered. FCD was gathered for a period of one week, as this amount seemed feasible regarding data size and sufficient for the current study. Only road sections which were part of a larger route were kept. Then, traffic data, speed data and road design data were linked to the road section. All road sections that missed data were then omitted. Finally, crash counts were linked to each road section and road section characteristics were linked to each individual crash. The final study area can be seen in figure 4, and includes 305 road sections and 1340 crashes.


*Figure 4: Final study area, 305 road sections, 1340 crashes*

Figures 5 through 8 show examples of the road sections that this study covers.

*Figure 5: N9 - © Rijkswaterstaat | Harry van Reeken*

*Figure 6: N99 - © Rijkswaterstaat | Harry van Reeken*

*Figure 7: N57 - © Rijkswaterstaat | Joop van Houdt*

*Figure 8: N36 - © R. Nägele*

# 5. Methodology

This research investigated the link between speed, crash likelihood and crash severity. The crash likelihood was determined with a negative binomial regression model with distance travelled by vehicles as control variable. The crash severity was determined with a logistic regression model.

Figure 9 below shows a short overview of the methodology of this research.

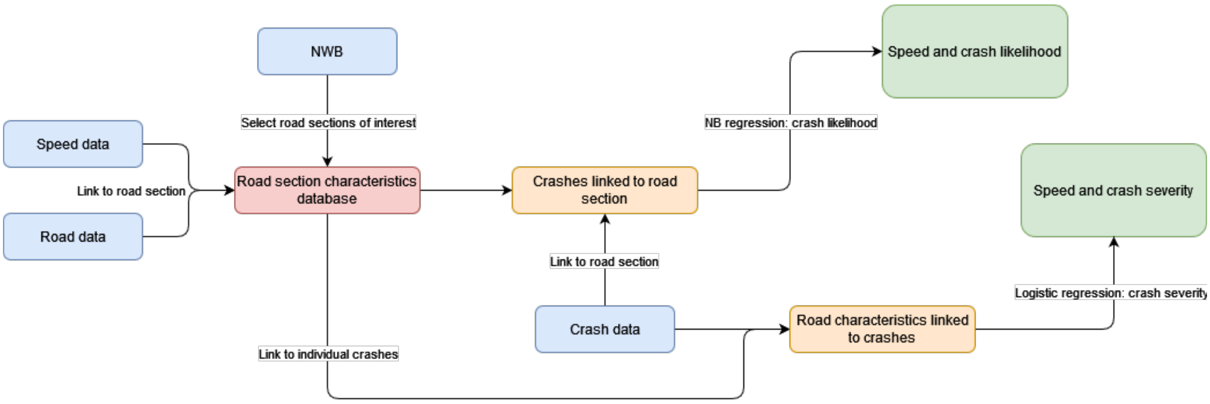


*Figure 9: Methodology*

## 5.1. Dependent variables

Using BRON information, the location of the crash was used to link the crash to a specific road segment. The crash severity was used to determine what type of crash occurred. Crashes were separated into fatal crashes and crashes resulting in injury (killed-and-injury (KI)), and crashes that result in property damage (property-damage-only (PDO)).

## 5.2. Independent variables

Several speed variables were considered as independent variables:

- The S85 (the speed that 85% of cars do not exceed)
- Deviation from the speed limit
- The standard deviation of speeds on a road section during the following four time periods as measure of temporal speed variation. The time sections are based on the ones that Rijkswaterstaat use (Rijkswaterstaat, sd):
  - Morning rush hour (06:00-9:59)
  - Day (10:00-14:59)
  - Evening peak (15:00-18:59)
  - Night (19:00-05:59)
- The coefficient of variation of speed between road segments as geographical measure of speed variation
- Speed limit

The sections below explain the calculation of the included speed variables and other variables.

### 5.2.1. Speed variables

#### 5.2.1.1. Driving speed variation

Speed variation can be included on a temporal basis (speed variation during a certain time period) or on a spatial basis (speed variation over a road).

*Standard deviation*

Speed variation over a certain time period is defined as the standard deviation of point speeds during a certain period (Xu, Wang, Yang, Xie, & Chen, 2019, p. 30). Here, these periods are determined as the morning and evening peak hours and off-peak hours. Point speeds are speeds at a specific location (Taylor, Lynam, & Baruya, The effects of drivers' speed on the frequency of road accidents, 2000, p. 6). This data is not available. Road sections were taken as the location. The standard deviation of speeds for each of the four time periods was calculated by taking individual minute measurements from floating car data, gathered by the NDW. These minute measurements were sorted into morning peak, day, evening peak, and night, adding all individual days together. The standard deviation of these values for each NBW road section was used. The standard deviation is referred to as SD and its general calculation is as follows:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

Here, $SD$ is the standard deviation, $n$ is the sample size, $x_i$ is an individual value, and $\bar{x}$ is the mean of all values.

*Coefficient of variation*

Speed variation over a road is commonly characterized by the coefficient of variation of speeds over a road (Taylor, Lynam, & Baruya, The effects of drivers' speed on the frequency of road accidents, 2000, p. 7). This coefficient of variation is the ratio of the standard deviation of speeds to the mean speed on a road. Though the road sections from the NWB form the basis, the road sections that the NDW use, to which speed characteristics are originally linked, are shorter and of a uniform length. This means that the road sections in this research contain several shorter NDW sections. This allows for a calculation of the coefficient of variation for all short sections in one longer NWB road section. The S85 yearly values for 2021 were taken for this calculation. The coefficient of variation was calculated by taking the standard deviation of the speed values and dividing that by the mean of the speed values. This coefficient of variation is referred to as CV and its general calculation is as follows:

$$CV = \frac{SD}{\mu}$$

Here, $CV$ is the coefficient of variation, $SD$ is the standard deviation of the S85 values on the NWB road section, and $\mu$ is the average of the S85 values on the NWB road section.

##### 5.2.1.2. Driving speeds

The average driving speed along each segment for each time period was used as an input variable. The annual value was taken, and the average of this value over the four-year study period was used. Values for the 24-hour period, the day and the night can be used. The driving speed was based on the same 2021 S85 values as for the CV.

##### 5.2.1.3. Deviation from the speed limit and speed limit

The deviation from the speed limit was calculated by subtracting the average driven speeds based on the NDW database from the speed limit, resulting in a positive value when driving speeds over the speed limit occurred, and a negative value when driving speeds under the speed limit occurred. The speed limit values were included per road section.

### 5.2.2. Traffic and road design variables

To account for the variation in segment length, the amount of daily vehicle kilometres travelled on average was calculated by multiplying the segment length with the daily average traffic volume, as has been done in other crash prediction models, like by (Kibar, Celik, & Aytac, 2013, p. 715). This gives the exposure of traffic for each segment. The vehicle kilometres were calculated based on vehicle count numbers from INWEVA for 2018 through 2021. The average value over these four years was calculated per road section. For the total vehicle count, freight count, medium weight vehicle count, and low weight vehicle count, the natural logarithm of the vehicle kilometres was taken for NB regression, which also accounts for the non-linear relationship between volume and crashes (Høye & Hesjevoll, 2020, p. 2).

The freight percentage was calculated by dividing the freight count by the total vehicle count and multiplying that by 100.

To decrease the likelihood of multicollinearity between road design variables and increase workability, VIND categorical variables for the general design were taken for most road design variables, such as the verge design, horizontal alignment, curve design, etc. Lane width, shoulder width, and median width were taken as numerical values.

VIND scores are present as values for intervals of 100 metres. This means that an average value needs to be used for all hectometres on one road section. However, as road sections can encompass a large number of VIND characteristics, the median of numerical values per road section was taken, as the median is not influences by a small proportion of extremely high or low values, like the average is.

The median value of the lane width in metres and shoulder width in metres per road section was directly used. Regarding the width of the median, a large value of 6.0 metres was assigned to lanes that are physically separated. All other widths were not changed. Then, the median value of median widths per road section is taken. Then, they are assigned to a dummy variable based on the statistical median of the median width. The reference value is 0.0-0.4m, then 0.4-0.8m, 0.8-1.0m, 1.0-2.0m, 2.0-5.0m, and >5.0m. This last value is associated with mainly physically separated carriageways.

The presence of a merging lane is coded as a dummy with 1 if there is one, and 0 if there is none. The horizontal alignment and verge design are classified red, orange, green and blue. The percentage of unsafe geometry is assumed to be relevant to crash risk. This means that the percentage of horizontal alignment and verge classified as red and orange per road section was determined by dividing the number of hectometres scored red for horizontal alignment and verge along a road section by the total number of hectometres along the road section. The same was be done for orange.

Literature on how to include junctions in general is limited. Several studies have been conducted on crash prediction models on and around intersections themselves, like (Abdel-Aty & Wang, 2006) and (Lord & Persaud, Accident Prediction Models With and Without Trend: Application of the Generalized Estimating Equations Procedure, 2000). However, they do not focus much on specific ways to include junctions in general crash prediction models. This research included junctions by calculating the junction density as junctions per kilometre, similar to the inclusion methods of previous studies on the number of exits and minor side roads per kilometre in (Greibe, 2003), or the number of different junctions per kilometre in (SWOV, 2017). The total number of junctions per road section was summed up and that value was divided by the road section length in kilometres.

## 5.3. Modelling approach

For crash likelihood analysis, Poisson and negative binomial regression methods are often used to estimate model parameters (Lord, Washington, & Ivan, Poisson, Poisson-gamma and zero-inflated regression models of motor vehicle crashes: balancing statistical fit and theory, 2005) (Tarko, Vilwock, & Blond, 2008, p. 31). The Poisson distribution assumes independency of events and equality of the mean and variance. However, this second assumption is often violated due to overdispersion, where the variance exceeds the mean (Hauer, 2015, p. 123). NB regression is a better choice, as it accounts for overdispersion. The basic form of most modern crash prediction models was used:

$$E(\lambda) = Q^{\beta} e^{\Sigma y_i x i}$$

Here, $E(\lambda)$ denotes the expected number of crashes and is based on traffic volume $Q$, raised to the power $\beta$. The risk factors that influence the crash probability are modelled as $e$ to the power of the sum of the independent variable values, $x_i$, and coefficients $y_i$ (Eenink, et al., 2008).

For crash severity analysis outcomes, binary or multinomial logistical models are often used (Eboli, Forciniti, & Mazzulla, 2020, p. 450) (Tarko, Vilwock, & Blond, 2008, p. 31) (Abdulhafedh, 2017, p. 200). A binomial logit regression model predicts the probability of a situation occurring or not (Lee & Abdel-Aty, 2008). In the current study, it is a crash being a KI or PDO crash. The model has the form (Dissanayake & Lu, 2002, p. 109):

$$\begin{aligned} Logit(p_i) &= \ln\left(\frac{p_i}{1-p_i}\right) \\ &= \alpha + \beta' X_i \end{aligned}$$

Here, $p_i$ is the probability of a binary response $y_i$ occurring ($y_i = y_1 | X_i$), with $y_i$ either being a KI or a PDO crash. $\alpha$ is the intercept parameter, $\beta'$ is a vector of the coefficients and $X_i$ is a vector of the independent variables.

The multinomial logit model is unordered, with the assumption that the unobserved factors are not correlated over the outcome (Ye & Lord, 2014, p. 73). It allows for more than two outcomes, thus can be used to make a distinction between fatal (K), injury (I), and PDO crashes. In addition, further outcomes like slight injury can be added. The model has the form (Savolainen, Mannering, Lord, & Quddus, 2011, p. 1671):

$$S_{in} = \beta_i X_{in} + \varepsilon_{in}$$

$$P_n(i) = \frac{e^{\beta_i X_{in}}}{\Sigma_i e^{\beta_i X_{in}}}$$

Here, $S_{in}$ is the injury outcome $i$ for observation $n$, with $\beta_i$ being a vector of parameters, $X_{in}$ being a vector of independent variables and $\varepsilon_{in}$ being a disturbance term that allows for unobserved effects. $P_n(i)$ is the probability of a certain injury outcome $i$ for observation $n$.

### 5.3.1. Multicollinearity

Multicollinearity is a problem in regression modelling, as the effect of the independent variables on the dependent variable is influenced by correlation between the independent variables, thus leading to inaccurate results or an inability to perform the regression (Daoud, 2017, p. 5). Multicollinearity was investigated through the use of a correlation matrix, on the basis of which variables can be altered or dropped from the list of predictor variables (Bayman & Dexter, 2021, p. 362).

### 5.3.2. Standardized coefficients

Because most independent variables are of a different magnitude or have different units, standardized coefficients are used to facilitate a visual comparison between the contribution of the individual variables to crash risk. To calculate the standardized coefficients, the following formula was used (Siegel & Wagner, 2022, pp. 371-431):

$$\beta_{st} = \frac{SD(x)}{SD(y)}\beta$$

Here, $\beta_{st}$ is the standardized coefficient of the independent variable, $SD(x)$ is the standard deviation of the independent variable, $SD(y)$ is the standard deviation of the dependent variable, and $\beta$ is the original coefficient from the regression analysis.

### 5.3.3. Software

Data processing and modelling was done in R. QGIS was used to visually display and interact with data like the road network, traffic intensity, etc. In addition, in case of spatial overlap, QGIS was used to link variables to road sections when it was not possible in R due to time constraints.

# 6. Results

## 6.1. Descriptive statistics

Table 3 shows summary statistics for multiple road design variables for the 305 road sections in the dataset.

| | *Min.* | *1st Qu.* | *Median* | *Mean* | *3rd Qu.* | *Max.* |
|---|---|---|---|---|---|---|
| *Road section length* | 10.360 | 139.760 | 326.820 | 758.930 | 1012.900 | 8182.800 |
| *Median width* | 0.000 | 0.680 | 6.000 | 3.587 | 6.000 | 6.000 |
| *Shoulder width* | 0.169 | 0.438 | 0.676 | 0.879 | 0.942 | 5.754 |
| *Lane width* | 1.662 | 3.088 | 3.207 | 3.293 | 3.403 | 6.782 |
| *Perc. horizontal all. red* | 0.000 | 0.000 | 0.000 | 2.094 | 0.000 | 100.000 |
| *Perc. verge red* | 0.000 | 31.480 | 50.000 | 49.380 | 75.000 | 100.000 |
| *Perc. verge orange* | 0.000 | 0.000 | 0.000 | 4.366 | 4.167 | 66.667 |

*Table 3: Summary statistics for multiple road design variables*

Figures 10 and 11 show the relationship between the CV of speeds and the number of crashes per vehicle kilometre and the relationship between the deviation from the speed limit value and the number of crashes per vehicle kilometre. Figure 12 shows the relationship between the SD during the four periods and the number of crashes per vehicle kilometre. The crashes per vehicle kilometre are the recorded number of crashes over a period of four years.

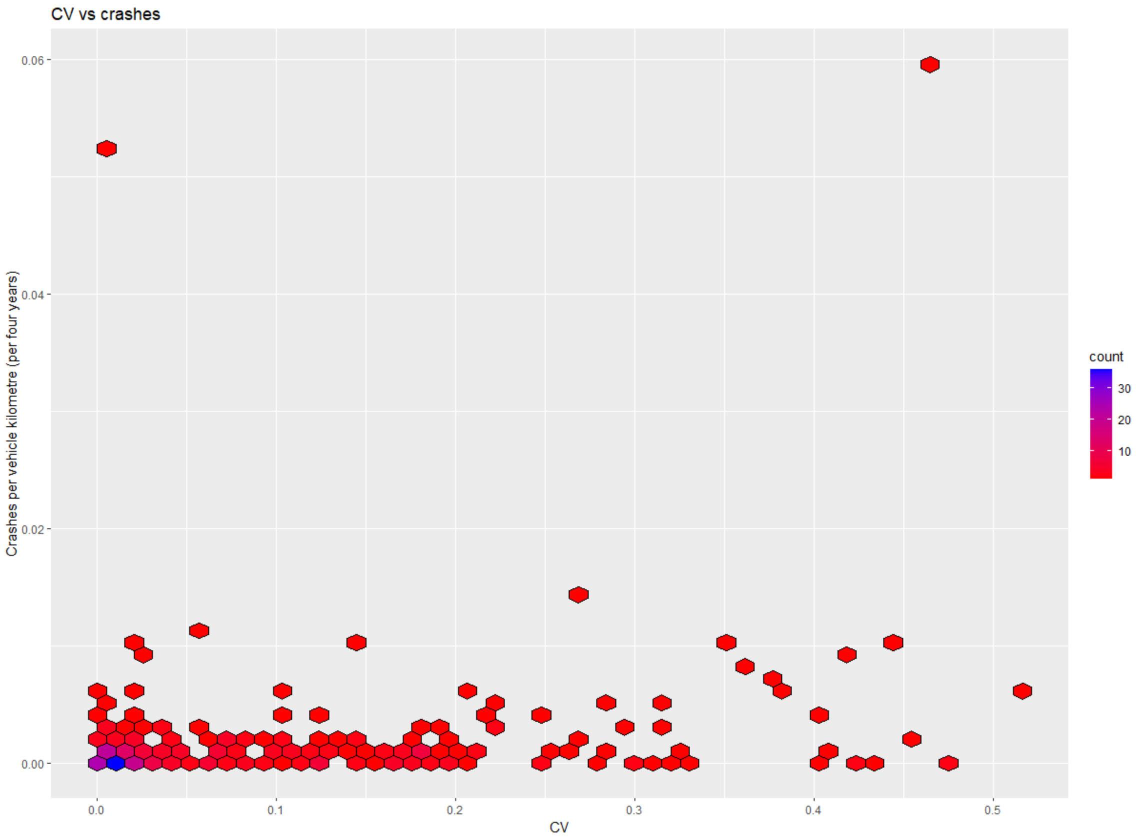


*Figure 10: CV of speeds versus the number of crashes per vehicle kilometre (for 2018 through 2021)*

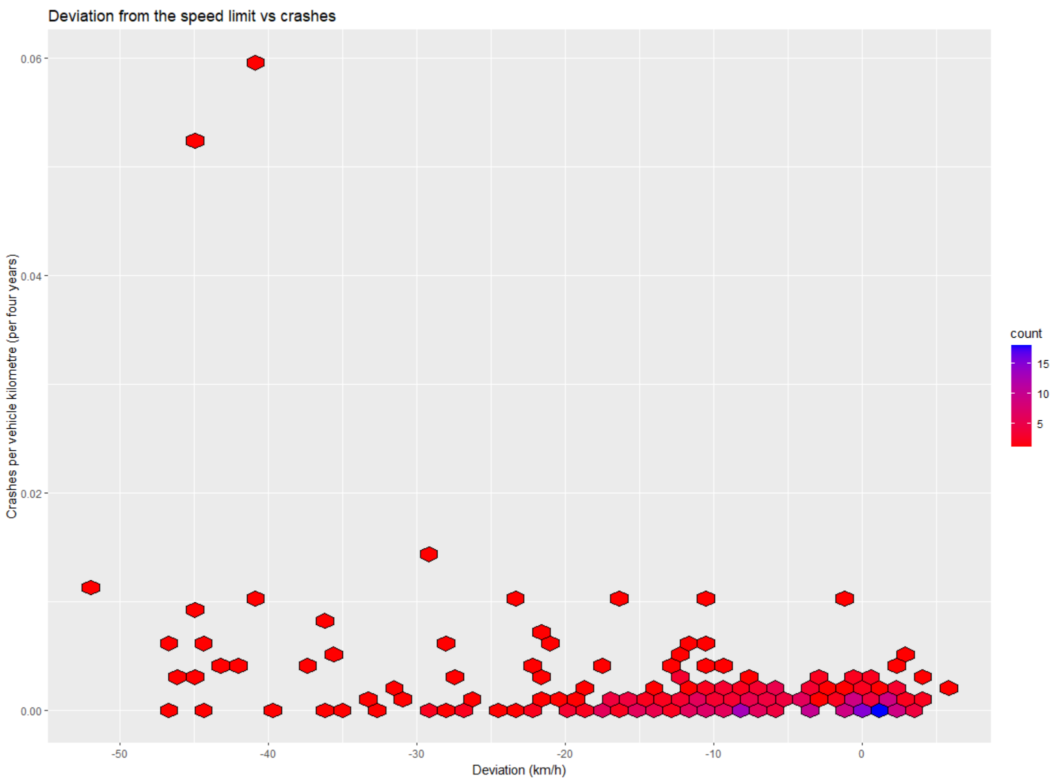


*Figure 11: Deviation from the speed limit versus the number of crashes per vehicle kilometre (for 2018 through 2021)*

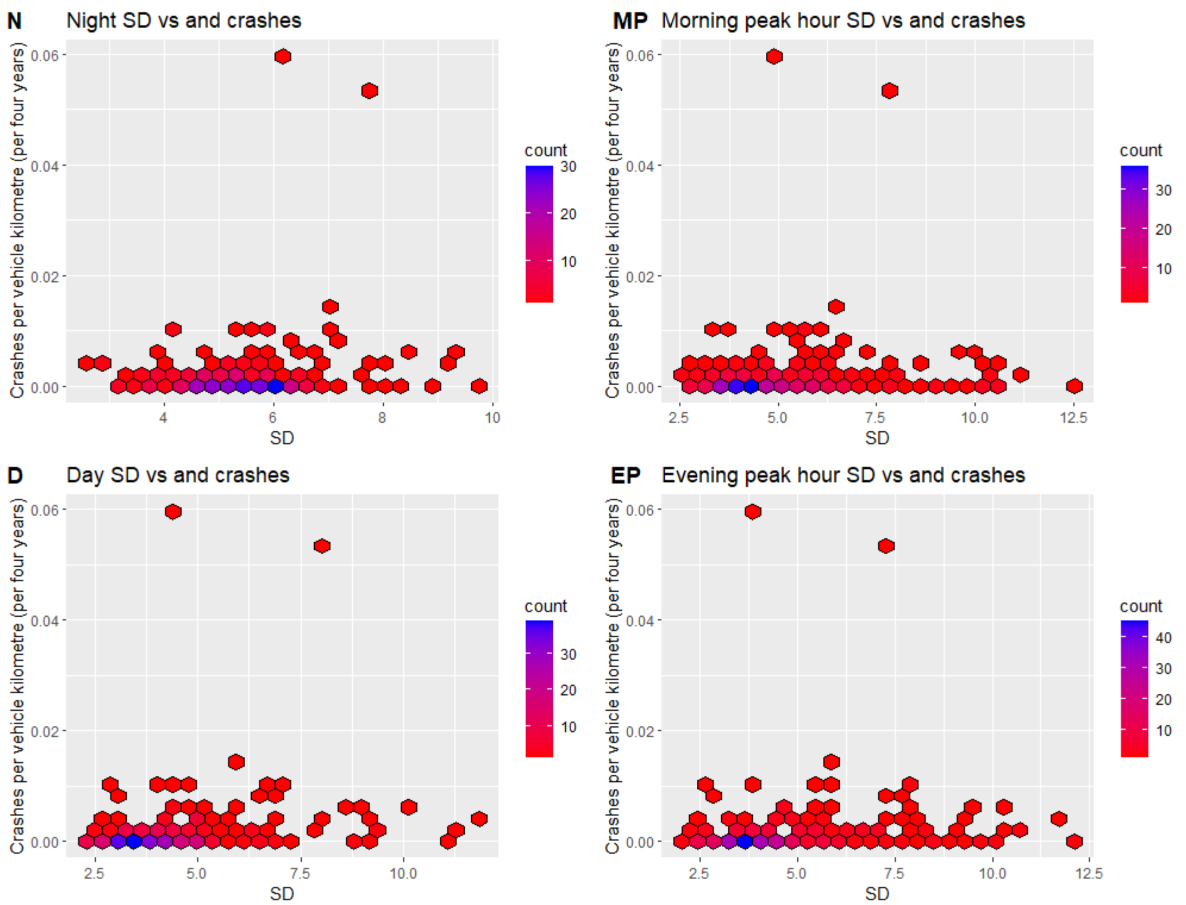


*Figure 12: SD night, morning peak, day, evening peak versus the number of crashes per vehicle kilometre (for 2018 through 2021)*

Figure 13 shows the distribution of the different crash severities for each of the recorded S85 speed bins. Regarding crash severity, 1 indicates a PDO crash, 2 indicates an I crash, and 3 indicates a K crash. Figure 14 shows how many road sections have had a certain number of crashes.

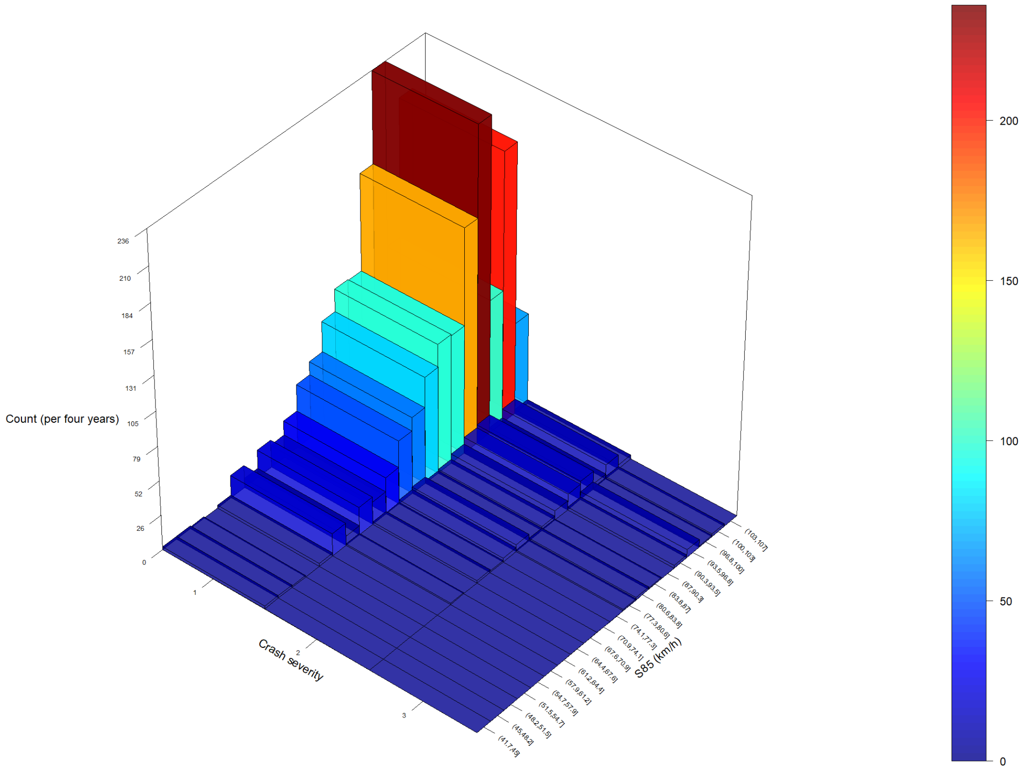


*Figure 13: Distribution of crash severities, 1=PDO, 2=I, 3=K (1340 crashes in total)*

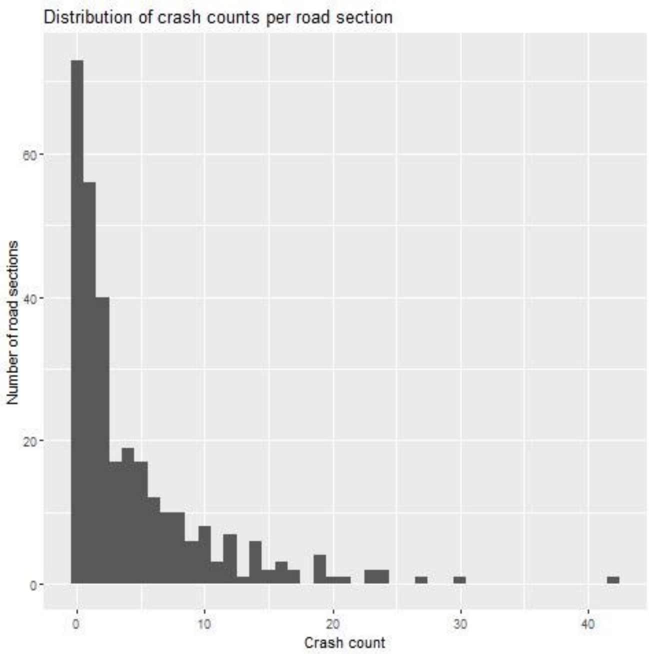


*Figure 14: Distribution of crash counts (305 road sections)*

## 6.2. Regression results

### 6.2.1. Negative binomial regression – crash likelihood

The results of the negative binomial regression to determine the relationship between the chosen independent variables and crash likelihood as the dependent variable are shown in the following sections.

Within the full set of independent variables, there was a large number of significant correlations between variables calculated from the same base values, for instance the vehicle kilometres for different vehicle types. These values were also correlated with the road section length. In addition, a lot of the speed variables were significantly correlated.

Figure 15 below shows the results for the correlation test for the speed variables. Only when correlations are -0.9 and lower and 0.9 and higher at the 5% confidence level, the potential multicollinearity was considered. This was also the case for the correlations between other non-speed variables.

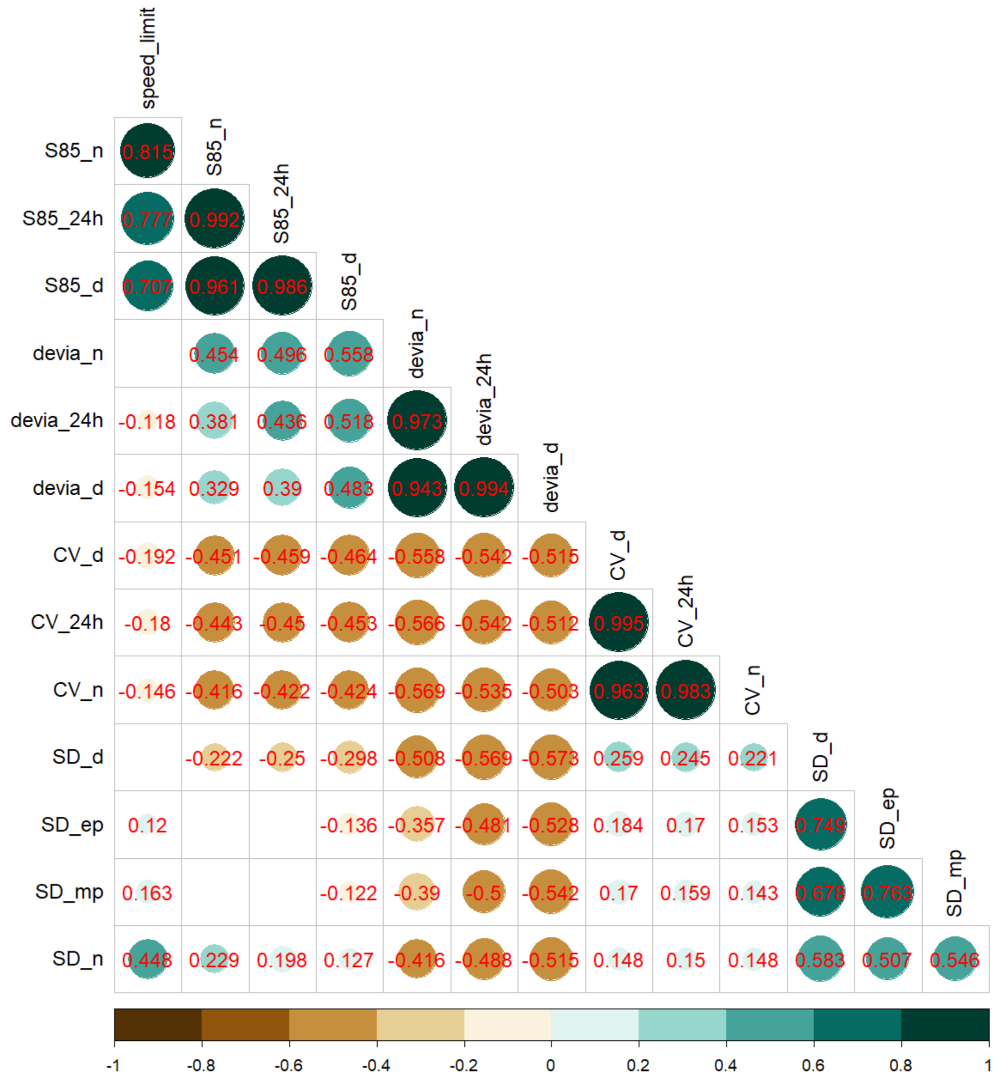


*Figure 15: Correlation matrix NB regression (correlation p ≤ 0.05)*

As the figure shows, there is quite a high level of correlation between the 24-hour variables and the day and night variables for most speed variables. To account for this, only the 24-hour speed variables for the road section CV, speed limit deviation, and S85 were included. In addition, though there is no sufficiently high statistical correlation between the maximum speed and other variables, it was excluded from the analysis on the basis of it logically being related to the deviation from the speed limit variable and S85 variable (which also shows a statistical correlation of around 0.8).

In combination with speed variable multicollinearity, there was also a high level of correlation between the vehicle kilometre values for different vehicle types and the total number of vehicle kilometres. To deal with this, the total number of vehicle kilometres was chosen, and the vehicle kilometres for different vehicle types were disregarded. Furthermore, the percentage of freight traffic was included, which did not show significantly strong correlation.

The results from the negative binomial regression for crash likelihood are shown in table 4 below. The unstandardized coefficient estimates are shown, with their standard errors and significance values.

*Table 4: NB regression crash likelihood results*

| | *Estimate* | *Std. Error* | *z value* | *Pr(>\|z\|)* | |
|---|---|---|---|---|---|
| *(Intercept)* | -4.60 | 0.90 | -5.11 | 3.21E-07 | *** |
| *SD evening peak* | 0.15 | 0.04 | 3.64 | 2.69E-04 | *** |
| *SD day* | 0.00 | 0.07 | 0.02 | 0.98 | |
| *SD morning peak* | -0.05 | 0.05 | -0.98 | 0.33 | |
| *SD night* | 0.04 | 0.09 | 0.39 | 0.70 | |
| *CV road section* | 0.88 | 0.61 | 1.43 | 0.15 | |
| *S85* | -0.02 | 0.01 | -2.54 | 0.01 | * |
| *Deviation from the speed limit (km/h)* | -0.01 | 0.01 | -1.08 | 0.28 | |
| *Freight perc.* | 0.01 | 0.02 | 0.54 | 0.59 | |
| *Shoulder width* | -0.17 | 0.10 | -1.83 | 0.07 | |
| *Lane width* | 0.16 | 0.16 | 1.00 | 0.32 | |
| *Merging lane* | 0.66 | 0.42 | 1.57 | 0.12 | |
| *Perc. horizontal all. red* | 0.01 | 0.01 | 1.80 | 0.07 | |
| *Perc. verge red* | -1.95E-03 | 2.13E-03 | -0.92 | 0.36 | |
| *Perc. verge orange* | 3.83E-03 | 0.01 | 0.68 | 0.50 | |
| *Median (0.4-0.8m)* | 0.20 | 0.18 | 1.11 | 0.27 | |
| *Median (0.8-1.0m)* | 0.14 | 0.20 | 0.74 | 0.46 | |
| *Median (1.0-2.0m)* | -1.98 | 0.76 | -2.60 | 0.01 | ** |
| *Median (2.0-5.0m)* | -4.19E-03 | 0.30 | -0.01 | 0.99 | |
| *Median (>5.0m)* | -0.03 | 0.18 | -0.19 | 0.85 | |
| *Junction density* | 2.47E-04 | 0.01 | 0.02 | 0.98 | |
| *ln(vehicle kilometres)* | 0.76 | 0.06 | 13.69 | 2.00E-16 | *** |

*'***': p≤0.001, '**': p≤0.01, '*': p≤0.05, '.': p≤0.1*
*2xlog-likelihood: -1300.32, theta: 2.99, std. err.: 0.52*

The regression analysis showed that the intercept, the SD of speed during the evening peak, the S85, a median width of 1.0 through 2.0 metres, and the vehicle kilometres are statistically significant at the 5% level. Regarding the speed variables, the SD of speed during the evening peak is relevant. It shows that a greater variation of speeds during the evening peak hours is correlated with an increased crash likelihood. Perhaps counterintuitively, road sections with an increased S85 (the speed that 85% of drivers do not exceed) are correlated with a lower crash likelihood.

Figure 16 below shows the standardized coefficients for each independent variable.

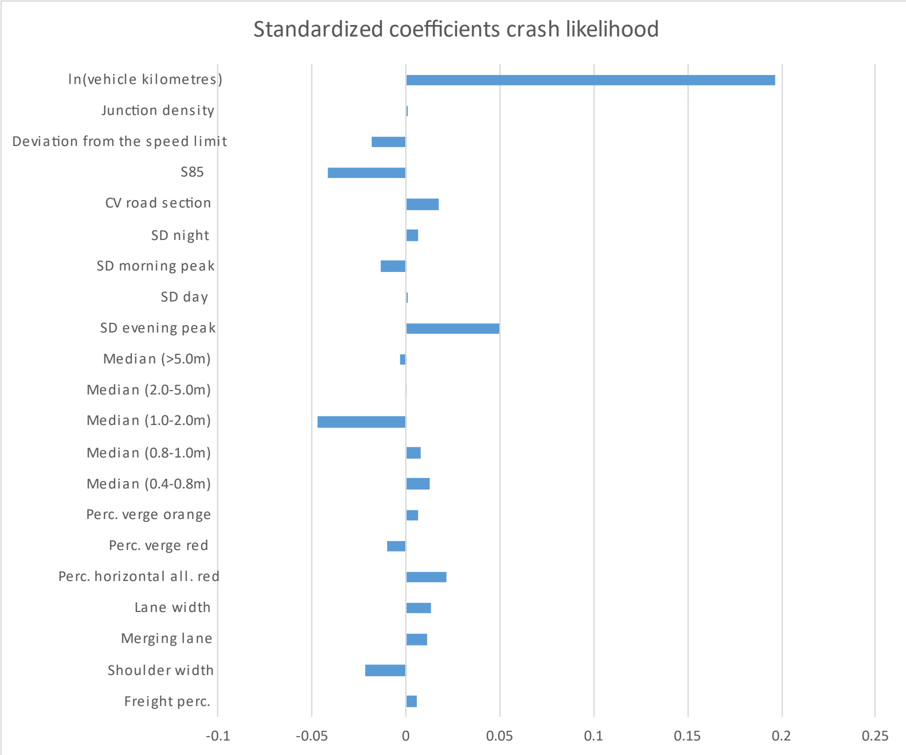

*Figure 16: Standardized coefficients NB regression for crash likelihood*

#### 6.2.1.1. Sensitivity analysis

A sensitivity analysis was performed for the standard deviation of speeds, to determine whether using a daily average or a peak and off-peak value showed a different relationship with crash likelihood, compared to values for four time sections. The results for the SD values can be seen in table 5. The full results can be found in appendix 10.2.

*Table 5: Results for SD variables in two new NB regression analyses on crash likelihood with different SD calculations*

| *Coefficients* | *Estimate* | *Std. Error* | *z value* | *Pr(>\| z\|)* | |
|---|---|---|---|---|---|
| *(1) Daily SD* | 0.18 | 0.05 | 3.37 | 7.40E-04 | *** |
| *(2) SD peak* | 0.12 | 0.04 | 2.67 | 0.01 | ** |
| *(2) SD off-peak* | 0.04 | 0.07 | 0.49 | 0.62 | |

The results for the first of the sensitivity analyses show that daily standard deviation of speeds is statistically significantly correlated with crash likelihood. The results for the second of the sensitivity analyses show that the standard deviation during peak hours is statistically significantly correlated with crash likelihood, while the standard deviation during off-peak hours is not.

### 6.2.2. Negative binomial regression – crash likelihood with interaction effects

The results from the negative binomial regression for crash likelihood with interaction effects between variables are shown in table 6 below. The unstandardized coefficient estimates are shown, with their standard errors and significance values. The interaction effects between speed and vehicle kilometres, speed and junction density, speed and verge design, speed and horizontal alignment, and speed and lane width were researched, as there is reason to suspect they influence each other, as was discussed in section 2.2.

*Table 6: NB regression crash likelihood results with interaction effects*

| | Estimate | Std. Error | z value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| (Intercept) | -10.45 | 4.29 | -2.44 | 0.02 | * |
| Speed*vehicle kilometres | -2.67E-03 | 3.90E-03 | -0.68 | 0.49 | |
| Speed*junction | 5.57E-04 | 1.42E-03 | 0.39 | 0.69 | |
| Speed*red verge | -3.56E-04 | 1.73E-04 | -2.06 | 0.04 | * |
| Speed*orange verge | -1.12E-03 | 5.45E-04 | -2.05 | 0.04 | * |
| Speed*shoulder width | 1.13E-03 | 0.01 | 0.22 | 0.83 | |
| Speed*horizon. all. | 4.76E-04 | 6.11E-04 | 0.78 | 0.44 | |
| Speed*lane width | -0.01 | 0.01 | -1.10 | 0.27 | |
| SD evening peak | 0.15 | 0.04 | 3.53 | 4.11E-04 | *** |
| SD day | 6.73E-05 | 0.07 | 1.00E-03 | 1.00 | |
| SD morning peak | -0.06 | 0.05 | -1.23 | 0.22 | |
| SD night | 0.01 | 0.10 | 0.13 | 0.90 | |
| CV road section | 0.49 | 0.65 | 0.75 | 0.45 | |
| S85 | 0.05 | 0.05 | 0.98 | 0.33 | |
| Deviation from the speed limit (km/h) | -0.01 | 0.01 | -1.39 | 0.17 | |
| Freight perc. | 0.02 | 0.02 | 0.73 | 0.46 | |
| Shoulder width | 1.08 | 0.67 | 1.61 | 0.11 | |
| Lane width | 1.08 | 0.67 | 1.61 | 0.11 | . |
| Merging lane | 0.79 | 0.42 | 1.90 | 0.06 | |
| Perc. horizontal all. red | -0.03 | 0.04 | -0.66 | 0.51 | |
| Perc. verge red | 0.03 | 0.02 | 1.88 | 0.06 | . |
| Perc. verge orange | 0.11 | 0.05 | 2.12 | 0.03 | * |
| Median (0.4-0.8m) | 0.07 | 0.18 | 0.40 | 0.69 | |
| Median (0.8-1.0m) | 0.02 | 0.20 | 0.08 | 0.94 | |
| Median (1.0-2.0m) | -2.26 | 0.81 | -2.79 | 0.01 | ** |
| Median (2.0-5.0m) | -0.11 | 0.31 | -0.36 | 0.72 | |
| Median (>5.0m) | -0.13 | 0.18 | -0.69 | 0.49 | |
| Junction density | -0.04 | 0.11 | -0.40 | 0.69 | |
| ln(vehicle kilometres) | 1.00 | 0.35 | 2.82 | 4.79E-03 | ** |

*'***': p≤0.001, '**': p≤0.01, '*': p≤0.05, '.': p≤0.1*
*2xlog-likelihood: -1290.05, theta: 3.15, std. err.: 0.55*

The regression analysis showed that the intercept, the interaction between speed and the percentage of verge graded red, the interaction between speed and the percentage of verge graded orange, the SD of speed during the evening peak, the percentage of verge graded orange, a median width of 1.0 through 2.0 metres, and the vehicle kilometres are statistically significant at the 5% level. Regarding speed variables, the interaction between speed and the percentage of verge graded red and the SD of speed during the evening peak is relevant. It shows that an increase in the combined effect of speed and red verge percentage are correlated with a lower crash likelihood, which can seem counterintuitive. In addition, an increased variation between speeds during the evening peak hours is correlated with a higher crash likelihood.

Figure 17 below shows the standardized coefficients for each independent variable, including interaction effect variables.

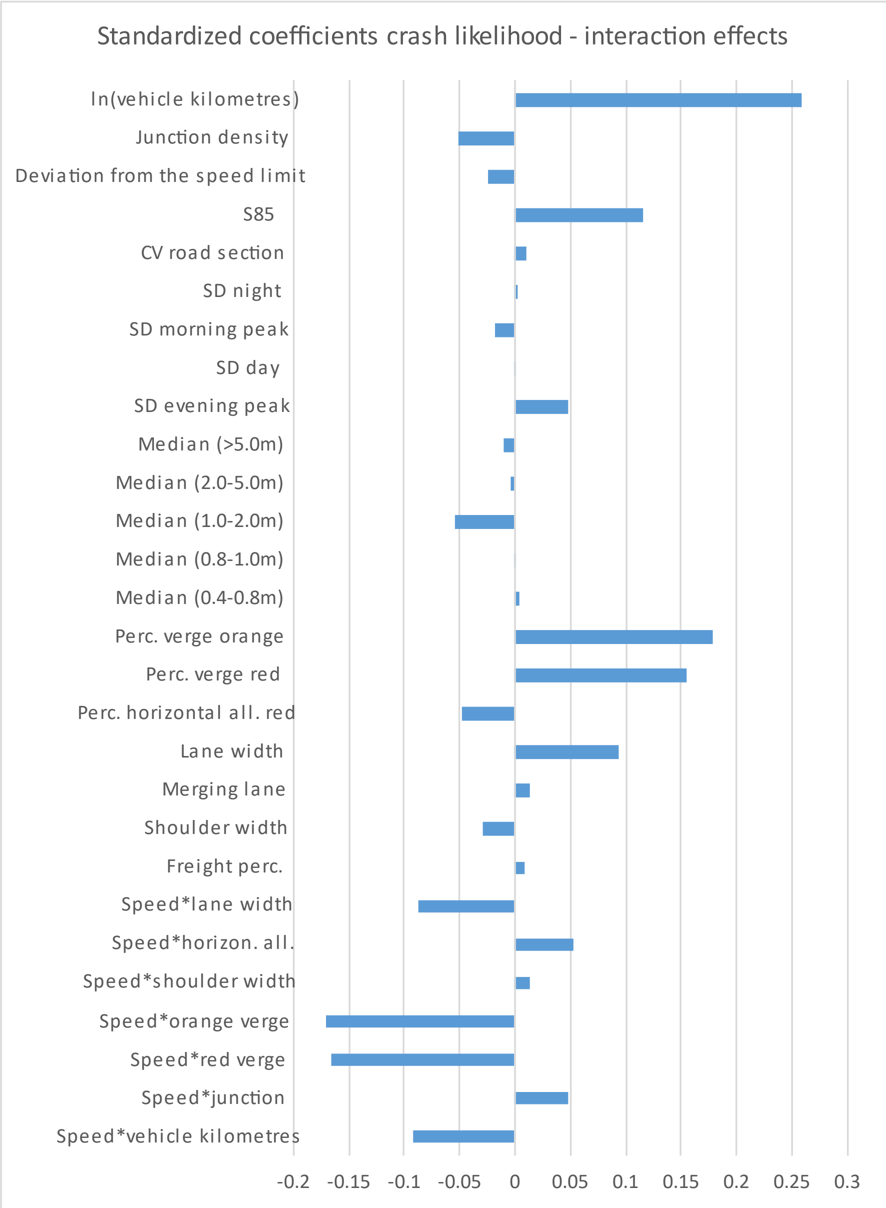


*Figure 17: Standardized coefficients NB regression for crash likelihood with interaction effects*

### 6.2.3. Logistic regression – crash severity

The results of the logistic regression to determine the relationship between the chosen independent variables and crash severity as the dependent variable are shown in the following sections.

As the independent variables have not changed, there is no need to perform another multicollinearity test. The previously calculated correlation matrix for speed variables can be found in section 6.2.1

Table 7 shows the results for the logistic regression on crash severity. The regression was done for PDO and KI crash outcomes. PDO is the reference level, and the exponent of the coefficients indicate the change in odds of a KI crash occurring compared to a PDO crash, when there is a one-unit increase in the independent variable.

*Table 7: Logistic regression crash severity results*

| | *Estimate* | *Std. Error* | *z value* | *Pr(>\|z\|)* | |
|---|---|---|---|---|---|
| *(Intercept)* | -2.75 | 2.89 | -0.95 | 0.34 | |
| *SD evening peak* | -0.02 | 0.11 | -0.16 | 0.87 | |
| *SD day* | 0.04 | 0.23 | 0.19 | 0.85 | |
| *SD morning peak* | -0.20 | 0.16 | -1.29 | 0.20 | |
| *SD night* | 0.04 | 0.29 | 0.13 | 0.89 | |
| *CV road section* | 1.93 | 2.09 | 0.92 | 0.36 | |
| *S85* | -2.08E-03 | 0.02 | -0.08 | 0.93 | |
| *Deviation from the speed limit (km/h)* | 0.01 | 0.03 | 0.28 | 0.78 | |
| *Freight perc.* | -0.02 | 0.07 | -0.31 | 0.75 | |
| *Shoulder width* | 0.33 | 0.30 | 1.09 | 0.27 | |
| *Lane width* | -1.58E-03 | 0.60 | -3.00E-03 | 0.99 | |
| *Merging lane* | -14.96 | 631.10 | -0.02 | 0.98 | |
| *Perc. horizontal all. red* | -0.07 | 0.05 | -1.43 | 0.15 | |
| *Perc. verge red* | 2.04E-03 | 0.01 | 0.32 | 0.75 | |
| *Perc. verge orange* | 0.02 | 0.01 | 1.58 | 0.12 | |
| *Median (0.4-0.8m)* | 0.52 | 0.43 | 1.21 | 0.23 | |
| *Median (0.8-1.0m)* | 0.58 | 0.50 | 1.15 | 0.25 | |
| *Median (1.0-2.0m)* | -16.51 | 2584.00 | -0.01 | 0.99 | |
| *Median (2.0-5.0m)* | 0.23 | 0.88 | 0.26 | 0.80 | |
| *Median (>5.0m)* | 0.05 | 0.51 | 0.10 | 0.92 | |
| *Junction density* | 0.10 | 0.04 | 2.63 | 0.01 | ** |
| *Vehicle kilometres* | 1.06E-05 | 1.44E-05 | 0.73 | 0.46 | |

*'***': p≤0.001, '**': p≤0.01, '*': p≤0.05, '.': p≤0.1*
*AIC: 638.41*

The regression analysis showed that only the junction density is statistically significant, with an increase in density being correlated with an increase in crash severity. This means that no statement regarding the effect of speed variables on crash likelihood can be made. The proportion of injury and fatal crashes in the dataset seems too low to achieve a sufficiently powers analysis on crash severity.

# 7. Discussion

The standard deviation during evening peak hours being the only statistically significant SD variable is an interesting result. Rear end crashes usually occur during congestion periods, mostly because drivers don't keep a safe distance between cars, are distracted, are not paying attention, or judge speed differences incorrectly (Tros, 2022, p. 5). The specific occurrence during this time could be due to time-of-day related factors such as a higher share of (mentally) fatigued drivers during the evening peak hours. Fatigue affects reaction time negatively (Lim & Dinges, 2008, pp. 312-313). In addition, fatigued drivers are less capable of judging distances to objects correctly (Liu & Wu, 2009, p. 1088). Fatigue also increases the frequency of hard-braking events (Mollicone, et al., 2019, p. 144), which are correlated with collisions and near-crashes (Dingus, et al., 2006). Finally, speed deviations are higher in fatigued driving and lane position of fatigued drivers are less stable compared to non-fatigued drivers (Liu & Wu, 2009, p. 1088), which could imply that more crash opportunities are present. These factors can exacerbate the effects of speed deviations already present, and combined can lead to a higher crash likelihood. Conversely though, the prevalence of fatigue in driving has been shown to be correlated with more personal characteristics, and not specific time-of-day factors, (Goldenbeld, Davidse, Mesken, & Hoekstra, 2011, p. 74), so the relative relationship between fatigue and the evening peak hours should be researched further.

The vehicle composition during the evening peak could also be different compared to other time periods, which could have an effect on crash likelihood. Another reason could be a different I/C (intensity/capacity) ratio during those hours, as the evening peak hours feature heavier traffic compared to other time periods (Rijkswaterstaat, 2023, p. 12). An increased I/C ratio is correlated with a higher crash likelihood as traffic volume reaches its capacity (Zhou & Sisiopiku, 1997, p. 51). However, these reasons are purely speculative, as more research is needed to determine what, if any, factors play a role in the specific effect of speed deviation during the evening peak.

The specific effect of the SD during evening peak in the original analysis, compared the aggregated peak and off-peak, and daily SD values in the sensitivity analysis, could be due to one or more of the limiting factors which are mentioned in section 7.1. Generally, though, this phenomenon requires further research.

The relationship between the S85 and the crash likelihood is counterintuitive, as higher speeds are expected to result in more and more severe crashes, which could be due to road users having to respond faster and a greater impact when a crash occurs. Possibly, this could be because road users adapt their speed based on road design and are more likely to speed on road sections they deem safe. This may explain the counterintuitive outcome in this correlational research. For instance, road users are more likely to drive faster if the road or shoulders are wider (SWOV, 2021, p. 14), or the lanes are wider (Ben-Bassat & Shinar, 2011, p. 2142). Wider lanes are correlated with lower crash rates on two-lane roads (Labi, 2011, p. 234). In addition, the absence of visual speed cues, like trees close to the roadside and a lack of built up environment, leads to a higher speed (SWOV, 2021, p. 14) (Iván & Koren, 2014, p. 9), but could also mean that there are less hazards to cause a crash or severe consequences (Kloeden, McLean, Baldock, & Cockington, 1999, p. 55). The result goes against previous research, which indicates that crash likelihood goes up when the speed increases, as has also been demonstrated with the Power Model (Elvik, 2013, pp. 858-859).

At first glance, wider medians (1.0 through 2.0 metres) being correlated with a decrease in crash likelihood compared to narrow medians (0.0 through 0.4 metres) seems logical, as drivers might have more room to veer from the road without crashing into opposite direction drivers. However, the outcomes are inconsistent as the results do not indicate a similarly decreased crash likelihood at road with an even wider median (more than 2.0 metres) or with separated carriageways. A wider median in general being safer fits with earlier research, where a wider median led to lower crash frequencies (Hadi, Aruldhas, Chow, & Wattleworth, 1995, pp. 175-176).

The negative relationship between the interaction effect of the S85 and verge design on crash likelihood is interesting when looking at the relation between the individual variables and crash likelihood, as an increase in speed and an increase in dangerous verges have both been shown to impact crash likelihood negatively (Elvik, 2013, pp. 858-859) (Kloeden, McLean, Baldock, & Cockington, 1999, pp. 3-4). This counterintuitive interaction effect could be due to the S85, which showed this same counterintuitive result in the regression without interaction effects. Though there are multiple other variables that showed a statistically significant correlation with crash likelihood when accounting for interaction effects, they will not be expanded upon. It seems counterintuitive to discuss individual effects that were not shown to be statistically significant in the analysis without interaction effects or reiterate previous statements about similar relationships.

A major suspected reason for the lack of significant results for the crash severity analysis is the distribution of crash outcomes in the dataset. This dataset includes mostly PDO crashes, as only 15 of the 1340 crashes were fatal, only 68 of the 1340 crashes resulted in injury, and 1257 resulted in property damage only. This means that there are very few KI outcomes that can be used to find patterns in the road section characteristics. The dataset is distributed too unevenly. The present study seems unsuitable to examine the relationship between speed and crash severity.

The results seem to show that only the number of junctions per kilometre is shown to have a statistically significant relationship with crash severity. This would mean that an increase in junction density is correlated with higher odds of a crash being a KI crash compared to a PDO crash. Considering the fact that the performed regression analysis does not seem suitable, doubt exists regarding the trustworthiness of this result. Thus, it will not be discussed further.

## 7.1. Limitations

One of the largest limitations in this research is its nature. This was a correlational study which cannot be used to determine causal relationships. It is not possible to account for all confounding factors that are not present in the model. This could explain some of the counterintuitive results. Other limitations could be the underreporting of crashes in BRON. The lack of registration of single-vehicle crashes can mean that crash patterns are less visible and higher crash severities are not recorded. It may also contribute to finding no relationship with factors that mainly contribute to these types of crashes. In addition, the dataset used to determine the standard deviation of the speeds is based on only one week of data. This means that the calculated values could be based on an outlier week. To minimize the chances of this happening, a week was chosen that has no school holidays, and major road works that could impact speed patterns were avoided. Furthermore, the S85 speeds were aggregated values, over a whole year. This smooths out any pattern that could have a time-specific effect. Finally, though section lengths were accounted for by using vehicle kilometres as exposure, rather than traffic volumes, aggregating data to different section lengths could have an impact on the contribution of other independent variables.

## 7.2. Future research

Based on the limitations, recommendations for future research include using a different database for crash records. Other databases might have a better registration of single-vehicle crashes, which could have an impact on crash hotspots and crash severity distributions. Crashes recorded by ambulances may become a suitable source in the future. Another recommendation is to look at a longer period for data used to calculate speed deviation data, as it could decrease the influence of outliers. For S85 data, however, it might be useful to take a less aggregated value, as too much smoothing could also distort the results. Regarding data organization, future research could look into different ways of aggregating road section characteristics, perhaps using smaller road sections or road sections of equal lengths. Additionally, further research can be done on the relationship between speed deviations and time of day, and the relationship between fatigue and peak hour driving. Lastly, the nature of the correlational relationships that were found in this study can be verified with other data.

# 8. Conclusion

The present study was designed to determine the relationship of speed variables with crash risk on 1x2 and 2x1 Rijkswaterstaat N-roads.

Two sub-questions were formulated to help reach this goal:

1) What is the relationship of the chosen speed variables with crash likelihood?
2) What is the relationship of the chosen speed variables with crash severity?

A statistically significant relationship between two speed variables and crash likelihood was found. One new statistically significant relationship between an interaction effect including a speed variable and crash likelihood was found when accounting for interaction effects. No statistically significant relationships between speed variables and crash severity were found.

The standard deviation during the evening peak is the only standard deviation variable that has a statistically significant relationship with crash likelihood. An increased crash likelihood with increasing speed variation is in line with what one would theoretically expect. As speed variation increases, road users have less time to respond to other road users' actions such as braking and overtaking with a higher speed difference. The results for the sensitivity analysis in section 6.2.1.1 show that the general standard deviation of speed is definitely statistically significantly correlated with crash likelihood, with a larger unstandardized coefficient for the combined values compared to that for the evening peak specific standard deviation. This implies that standard deviation always plays a role, during more time periods than just the evening peak. In addition, there is reason to suspect that standard deviation during peak hours is correlated with crash likelihood, while off-peak standard deviation is not.

The S85 is the second speed variable that has a statistically significant relationship with crash likelihood, where an increase in speed is correlated with a counterintuitive decrease in crash likelihood.

Additionally, a road section with a median width of 1.0 through 2.0 metres has a negative relationship with crash likelihood compared to a road section with a median width of 0.0 through 0.4 metres, meaning that an increase in sections with a median width of 1.0 through 2.0 metres is correlated with a lower crash likelihood. An increase in vehicle kilometres travelled along a road section has been found to be correlated with a higher crash likelihood. This result is fairly straightforward, as more driving on the road means more cars to potentially crash into. The result fits within earlier research, as it has indicated that exposure plays a significant role in crash frequency.

An increase in the combination of the S85 and the percentage of verge classified as red and an increase in the combination of the S85 and the percentage of verge classified as orange are correlated with a decrease in crash likelihood when taking interaction effects into account.

In conclusion, the variables standard deviation of speeds during the evening peak and the S85 of speeds are important speed factors to consider when aiming to reduce crash occurrence. Reducing crash occurrence in general might help towards reaching the goal of halving traffic fatalities by 2030.

## 8.1. Practical recommendations

When looking at practical recommendations to reduce crash likelihood and potentially reduce crash severity on Rijkswaterstaat N-roads, multiple measures are suggested based on the results for the speed variables, and traffic and road characteristic variables. Firstly, implementing measures that reduce speed deviation, especially during evening peak hours, could lead to a reduction in crash likelihood. Trajectory speed control measures, which measure speed over a longer distance, have shown to decrease accidents (Kennisnetwerk SPV, sd), which could be due to a uniform speed pattern, which lends itself to use for this purpose as well. In addition, ISAs (Intelligent Speed Adaptation systems) have shown to decrease the number of fatal accidents by informing drivers of speed violations, though their effect on speed deviation has not been determined (SWOV, sd). Furthermore, measures to reduce tailgating could decrease speed deviation, as drivers keep a constant distance from their lead vehicle. Measures that proved effective on Pennsylvania and Minnesota high speed rural roads included dots as pavement markings and signs directed at drivers to keep two dots between them and the vehicle in front (Gorrill, 2008, pp. 3, 5). Secondly, redesigning verges to comply with the highest design requirements could also lead to a reduction in crash severity. Thirdly, reducing junction density by turning at-grade junctions and pedestrian crossings into grade separated junctions, like proposed in the measures described in section 1, could decrease crash likelihood and severity. Fourthly, avoiding narrow medians where possible could lead to a reduction in crash likelihood. Finally, the presence of a statistically significant correlation between speed variation and crash likelihood lends credibility to the inclusion of speed deviation variables in the VIND.

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# 10. Appendices

## 10.1. VIND criteria for included categorical variables

*Table 8: VIND criteria (translated from (de Boer, 2023))*

| *Variable* | *Road type/speed limit* | *Good* | *Safety management attention area* | *Inadequate* |
|---|---|---|---|---|
| *Verge design* | 90/100 km/h | Straight road section or spacious bend with an obstacle-free zone of at least 10 metres | Straight road section or spacious bend with an obstacle-free zone of 8-10 metres:<br>- High risk: unmovable object<br>- Medium risk: fencing, etc.<br>- Low risk: objects that do not pose any risk, provided they are placed properly | Straight road section or spacious bend with an obstacle-free zone of less than 8 metres:<br>- High risk: unmovable object<br>- Medium risk: fencing, etc.<br>- Low risk: objects that do not pose any risk, provided they are placed properly |
| | 70/80 km/h | Straight road section or spacious bend with an obstacle-free zone of at least 6 metres | Straight road section or spacious bend with an obstacle-free zone of 4,5-6 metres:<br>- High risk: unmovable object<br>- Medium risk: fencing, etc.<br>- Low risk: objects that do not pose any risk, provided they are placed properly | Straight road section or spacious bend with an obstacle-free zone of less than 4,5 metres:<br>- High risk: unmovable object<br>- Medium risk: fencing, etc.<br>- Low risk: objects that do not pose any risk, provided they are placed properly |
| *Horizontal alignment* | 90/100 km/h | Bend R>500 m | Sharp bend in continuous roadway (R<500 m) where all compensating measures are applied | Sharp bend in continuous roadway (R<300 m)<br>OR<br>Sharp bend in continuous roadway (R<500 m) where not all compensating measures are applied:<br>- Demarcation and marking according to norms for sharp bends<br>- Skid resistance index >0,03<br>- Cant > norm<br>- Outside of bend shielded throughout the entire bend |

| | | | | |
|---|---|---|---|---|
| | | | | (motorcycle friendly) or a 13 metres wide obstacle free zone without any of these objects up to 20 metres from the outside roadside:<br>o Unshielded (crash safe) objects<br>o Steep slope<br>o Deep waterway |
| | 70/80 km/h | Bend R>300 m | Sharp bend in continuous roadway (R<300 m) where all compensating measures are applied | Sharp bend in continuous roadway (R<170 m)<br>OR<br>Sharp bend in continuous roadway (R<300 m) where not all compensating measures are applied:<br>- Demarcation and marking according to norms for sharp bends<br>- Skid resistance index >0,03<br>- Cant > norm<br>- Outside of bend shielded throughout the entire bend (motorcycle friendly) or a 13 metres wide obstacle free zone without any of these objects up to 20 metres from the outside roadside:<br>o Unshielded (crash safe) objects<br>o Steep slope<br>o Deep waterway |
| *Mark all road sections with a speed limit of <70 km/h with the colour blue* | 50/60 | | | |

## 10.2. Results sensitivity analysis

Tables 9 and 10 show the results for the sensitivity analysis performed for different time periods for the standard deviation of speeds in section 6.2.1.1.

*Table 9: NB regression crash likelihood results – daily SD*

| | *Estimate* | *Std. Error* | *z value* | *Pr(>\|z\|)* | |
|---|---|---|---|---|---|
| *(Intercept)* | -4.98 | 0.90 | -5.56 | 2.77E-08 | *** |
| *Daily SD* | 0.18 | 0.05 | 3.37 | 7.40E-04 | *** |
| *CV road section* | 0.94 | 0.62 | 1.51 | 0.13 | |
| *S85* | -0.02 | 0.01 | -2.51 | 0.01 | * |
| *Deviation from the speed limit (km/h)* | -0.01 | 0.01 | -0.89 | 0.37 | |
| *Freight perc.* | 0.01 | 0.02 | 0.30 | 0.76 | |
| *Shoulder width* | -0.20 | 0.10 | -2.03 | 0.04 | * |
| *Lane width* | 0.18 | 0.16 | 1.14 | 0.25 | |
| *Merging lane* | 0.67 | 0.42 | 1.59 | 0.11 | |
| *Perc. horizontal all. red* | 0.01 | 0.01 | 1.65 | 0.10 | . |
| *Perc. verge red* | 0.00 | 0.00 | -1.00 | 0.32 | |
| *Perc. verge orange* | 0.00 | 0.01 | 0.62 | 0.54 | |
| *Median (0.4-0.8m)* | 0.20 | 0.18 | 1.12 | 0.26 | |
| *Median (0.8-1.0m)* | 0.12 | 0.20 | 0.63 | 0.53 | |
| *Median (1.0-2.0m)* | -1.94 | 0.76 | -2.55 | 0.01 | * |
| *Median (2.0-5.0m)* | -0.01 | 0.30 | -0.02 | 0.98 | |
| *Median (>5.0m)* | -0.04 | 0.17 | -0.21 | 0.83 | |
| *Junction density* | 1.69E-03 | 0.01 | 0.14 | 0.89 | |
| *ln(vehicle kilometres)* | 0.77 | 0.05 | 14.40 | 2.00E-16 | *** |

*'***': p≤0.001, '**': p≤0.01, '*': p≤0.05, '.': p≤0.1*
*2xlog-likelihood: -1306.76, theta: 2.86, std. err.: 0.49*

*Table 10: NB regression crash likelihood results – peak and off-peak SD*

| | *Estimate* | *Std. Error* | *z value* | *Pr(>\|z\|)* | |
|---|---|---|---|---|---|
| *(Intercept)* | -4.92 | 0.90 | -5.47 | 4.48E-08 | *** |
| *SD peak* | 0.12 | 0.04 | 2.67 | 0.01 | ** |
| *SD off-peak* | 0.04 | 0.07 | 0.49 | 0.62 | |
| *CV road section* | 0.96 | 0.62 | 1.55 | 0.12 | |
| *S85* | -0.02 | 0.01 | -2.30 | 0.02 | * |
| *Deviation from the speed limit (km/h)* | -0.01 | 0.01 | -1.08 | 0.28 | |
| *Freight perc.* | 0.01 | 0.02 | 0.23 | 0.82 | |
| *Shoulder width* | -0.21 | 0.10 | -2.15 | 0.03 | * |
| *Lane width* | 0.19 | 0.16 | 1.18 | 0.24 | |
| *Merging lane* | 0.69 | 0.42 | 1.64 | 0.10 | |
| *Perc. horizontal all. red* | 0.01 | 0.01 | 1.61 | 0.11 | |
| *Perc. verge red* | -2.16E-03 | 2.12E-03 | -1.02 | 0.31 | |
| *Perc. verge orange* | 3.15E-03 | 0.01 | 0.55 | 0.58 | |
| *Median (0.4-0.8m)* | 0.19 | 0.18 | 1.06 | 0.29 | |
| *Median (0.8-1.0m)* | 0.12 | 0.19 | 0.62 | 0.53 | |
| *Median (1.0-2.0m)* | -1.95 | 0.76 | -2.57 | 0.01 | * |
| *Median (2.0-5.0m)* | -0.01 | 0.30 | -0.03 | 0.98 | |
| *Median (>5.0m)* | -0.04 | 0.17 | -0.24 | 0.81 | |
| *Junction density* | 1.71E-03 | 0.01 | 0.14 | 0.89 | |
| *ln(vehicle kilometres)* | 0.76 | 0.05 | 14.29 | 2.00E-16 | *** |

*'***': p≤0.001, '**': p≤0.01, '*': p≤0.05, '.': p≤0.1*
*2xlog-likelihood: -1306.24, theta: 2.90, std. err.: 0.50*