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Kröyer, Höskuldur

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DEPARTMENT OF TECHNOLOGY AND SOCIETY | LUND UNIVERSITY 2015

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The results show that there is a positive correlation between the exposure of pedestrians, bicyclists and motorized vehicles and the number of accidents, i.e. the more road users there are, the more accidents occur. The models also suggest that this relation is non-linear; the accident risk per road user is lower at sites where the exposure is greater (safety in numbers effect). Furthermore, the results show safety in numbers effect for single pedestrian accidents, which might suggest that the underlying reasons for this effect is more complex than previously assumed.

The thesis suggest an alternative way to interpret risk values and risk curves for injury severity/outcome (if one is involved in an accident), in which differences arise depending on whether the aim is to interpret the relation from an individual perspective or from the perspective of society as a whole. The results furthermore show a strong correlation between the speed environment, the age of the victim and the injury severity/outcome. A considerable proportion of the serious injuries occurs in low speed environments, seniors suffer more serious injuries than younger pedestrians and cyclists do, and the effects differ substantially for struck pedestrians versus struck bicyclists.

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Content

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Glossary and abbreviations

Abbreviated Injury Scale, AIS:	An injury classification system for describing injuries incurred in traffic accidents. The injuries are coded with regard to type of injury, body part injured and injury severity.
Accident migration:	When a reduction in the number of traffic accidents at one site or within one road user group results in an increase in accidents at another site or in another group.
Accident mechanisms:	The motions and contacts/impacts that occur during a collision and the forces of those impacts.
Accident prediction model:	A mathematical model meant to describe how the number of accidents relates to various factors, often with the aim of predicting the number of accidents (also referred to as safety performance function).
Absolute risk curve:	The probability of a given injury if involved in an accident against some other variable (e.g. speed). The term absolute refers to the curve´s presentation of the probability of given injury as a percentage.
Base speed:	In hypothetical scenarios with different speed levels, base speed refers to the speed in the reference situation.
Behavior:	An individual´s actions, whether at the moment of accident or during normal driving/travel. The term can refer to one action or to a general pattern of actions.
Consequence:	The injury severity/outcome of an accident. Often described as the probability of a given injury severity/outcome (sometimes as a risk curve).
Contributory factor/variable:	A factor/variable that influences the dependent variable.
Exposure:	The quantity of events or travel that can result in an accident. This can be the number of road users,

	distance travelled or number of events (e.g. interactions).
Free vehicle:	A vehicle whose movement is not influenced by that of other nearby vehicles.
Geometric variable:	A variable meant to describe a specific attribute of the physical traffic environment.
Impact speed:	The speed of a vehicle or road user at the moment of collision (at first contact).
In-depth accident database:	An accident database that lists detailed description of accidents collected by experts who visit accident sites immediately after an accident has occurred.
Injury outcome:	The consequences of the injury, often described by probability of fatality or disability if a person is injured or involved in an accident. This descriptor combines injury severity with individual´s preconditions.
Injury outcome model:	A model that describes the consequence dimension (see consequence), i.e. the probability of given injury severity/outcome once a person is involved in an accident based on contributory variables.
Injury severity:	A measure that describes how serious the injuries are, independently of individual characteristics, i.e. the injury severity may be the same for two individuals, but their outcomes will differ depending on their individual preconditions.
Injury Severity Score, ISS:	Rating of injury severity based on the AIS scale (Abbreviated Injury Scale). A measure aimed to better take into consideration the fact that the victim may suffer multiple injuries.
Light truck vehicle, LTV:	Trucks or truck like vehicles, including among others pick-ups, vans and sport utility vehicles (SUV). Note that the definitions varies between different studies.
Main street:	A street that is aimed at serving through traffic and connecting city districts.
Max AIS, MAIS:	A measurement to describe the injury severity. The MAIS is equal to the highest AIS injury value the individual suffers.

Mean travel speed:	The mean spot speed of all passing vehicles at a single location.
Modal share/split:	The proportion of travels by different travel modes.
Morbidity:	Refers to the state of health, can refer to injury, disability or diseases.
Objective safety:	The measureable accident situation, i.e. the number of accidents, the risk of being involved in an accident and the probability of sustaining an injury of a certain injury severity.
Overrepresentation:	If a group constitutes a proportion of some accident type greater than the same group´s proportion of the total population, they are overrepresented in that accident type.
Reaction distance:	The distance travelled during the reaction time.
Reaction time:	The time it takes from the moment a driver notices something until he or she takes some action (e.g. braking).
Relative fatality risk curve:	The proportional changes in fatality risk for given change in speed, based on an absolute fatality risk curve.
Relative speed:	The proportional difference in speed before and after some (hypothetical) change in speed (V_{after}/V_{before}).
Reporting degree:	The proportion of registered accidents (i.e. accidents included into the database) compared to the actual number of accidents that occur (many of which are never reported).
Risk:	The term risk is used here for two separate purposes: (1) to discuss the probability of being involved in an accident (i.e. the number of accidents related to exposure), and (2) to describe the overall probability (risk) of sustaining a certain injury when one is involved in an accident (e.g. if involved in a collision there is 10% probability (risk) of sustaining a serious injuries). The former definition is usually applied when discussing the risk dimension; the latter definition is usually applied when discussing the consequence dimension.

Risk curve:	Frequently used to describe the consequence dimension, the risk curve demonstrates the probability of a given injury severity/outcome for a person if involved in an accident, against some other factor (e.g. impact speed). Usually presented as a mathematical model or an x-y graph.
Safety in numbers:	The phenomenon that the number of accidents for a given road user group does not increase proportionally as fast as the number of those road users.
Safety performance function:	A mathematical model meant to describe how the number of accidents relates to exposure and various factors, often with the aim of predicting the number of accidents (see also accident prediction model).
Speed distribution:	All measured speed values sorted by their frequency, to indicate the actual speed situation.
Sport utility vehicles, SUV:	A relatively large vehicles, often higher than other passenger vehicles, designed for rough surfaces (Note that definitions vary).
Subjective safety	Refers to the perceived or 'felt' safety for an individual or a group.
STRADA:	Swedish Traffic Accident Data Acquisition. An accident database that aims to include all traffic accidents involving injuries that occur in Sweden and are registered by hospital or police.
Time trend bias:	The phenomenon that (in this case) accident data from one year is not necessarily compatible with accident data from another year. The reason for this is that the number (and the injury severity/outcome) of accidents is continually changing owing to changes in infrastructure, behavior and population, resulting in bias if accident data from two periods are compared.
Traffic accident:	An incident that is unexpected and unintentional and that may result in injuries. In this thesis, single pedestrian accidents are included in this definition.
Traffic conflict:	An event, involving two or more road users, that will result in an accident if no one takes some evasive action (brakes, swerves, or accelerates).

Travel speed:	In this work, travel speed refers to how fast a vehicle is moving before a traffic conflict occurs or before a road user takes evasive actions.
Underrepresentation:	If a group accounts for a smaller proportion of some accident type than its proportion of the total population, it is underrepresented in that accident type.
Underreporting:	Refers to that not all accidents are reported, and some are missing from accident databases (see reporting degree).
Vision Zero:	The Swedish parliament decided in 1997 that no one should suffer serious or fatal injuries in traffic. This vision is the guiding policy of traffic safety work in Sweden.

List of publications

Paper I: Kröyer, H.R.G., 2015. Pedestrian and bicyclist flow in accident modelling at intersections. Influence of the length of observation period. Re-submitted to Safety Science.

Paper II: Kröyer, H.R.G., Jonsson, T., Várhelyi, A., 2014. Relative fatality risk curve to describe the effect of change in the impact speed on fatality risk of pedestrians struck by a motor vehicle. Accident Analysis & Prevention, 62, 2014, pp. 143-152. *My contribution: I designed the study, performed all the analyses and was the main author of the paper.*

Paper III: Kröyer, H.R.G., 2015. Is 30 km/h a ´safe´ speed? Injury severity of pedestrians struck by a vehicle and the relation to travel speed and age. IATSS Research 39, pp. 42-50.

Paper IV: Kröyer, H.R.G., 2015. The relation between speed environment, age and injury outcome for bicyclists struck by a motorized vehicle – A comparison with pedestrians. Accident Analysis & Prevention, 76, 2015, pp. 57-63.

1. Introduction

Everybody needs to travel, whether for pleasure or for business; it is one of our basic needs. However, this travelling comes with a price. In Sweden, hundreds of lives are lost every year and thousands of people are seriously injured in traffic accidents (TRAFA, 2015). This side effect, however, is not something that must simply be accepted. It is preventable, or can at least be reduced. Achieving this requires influencing road user behavior and the traffic environment so as to it minimize the risk of a traffic accident occurring (a traffic accident being an incident that is unexpected and unintentional and may result in injuries, including single pedestrian accidents) and to minimize the severity of the injuries if an accident does occur. Since preventing all accidents might be ´impractical´ or impossible, the main goal of the Swedish transport safety policy, called *Vision Zero*, is that no serious or fatal injuries should occur in the traffic (Proposition 1996/97:137).

Even though we have not reached the goal, this process of pursuing it is well under way regarding fatal accidents. In 1996 there were over 500 fatal traffic accidents, whereas in 2014 the number had been reduced to 270 (TRAFA, 2015); the aim is to further lower such incidents to 220 by the year 2020 (The Swedish Transport Administration, 2012). There has also been substantial reduction in the number of serious injuries, even though not as great as for the fatal accients (The Swedish Transport Administration, 2012, TRAFA, 2015). When focusing on pedestrians and bicyclists, the number of fatal accidents decreased between 1996 and 2008/2009, but whereas fatalities for motor vehicle occupants have continued to decrease since then, the reduction for pedestrians and bicyclists seems to have halted, or at least slowed noticeably (TRAFA, 2015).

The reason for this plateau might be that those groups have not received sufficient focus in the safety work, or that there are reasonable reasons why the decrease in fatal pedestrian and bicycle accidents have halted; however, even so, we must succeed in reducing those accidents too. This failure to prevent fatal accidents for pedestrians and bicyclists is all the more troubling because these are our most fundamental mode of travel (several groups rely on walking and cycling as their only available travel mode) and because pedestrians and bicyclists are more vulnerable in accidents than individuals driving or riding in motorized vehicles are (Richards, 2010). Moreover, the problem is unlikely to disappear since Sweden aims to increase the modal share of walking and bicycling in urban settings in the future, because these travel modes have positive effects on the urban environment and public health.

Creating a safe environment in which accident cost will decrease requires understanding what influences the risk of an accident occurring and the consequences of such accidents (i.e. how serious the injuries are and the injury outcome). This study explores ways that various factors influence the traffic safety of pedestrians and bicyclists, concentrating on collisions with motorized vehicles, in order to better understand why these accidents occur and how the number of serious and fatal injuries can be reduced. The main focus will be on (a) the relation between the number of road user and the number of accidents and (b) how speed environment and age is related to the injury severity/outcome, if involved in an accident, along with the implications of that relation for the speed policy.

1.1 Accident statistics

In studying pedestrian and bicycle accidents, the first challenge is obtaining information regarding the number of accidents and details about them. The Swedish Transport Agency maintains an accident database, the *Swedish Traffic Accident Data Acquisition (STRADA)*, which aims to collect reports from police and hospitals on every traffic accident in Sweden in which an injury occurs (SOU 2014:24). The data includes, among other things, the date and time when the accident occurred, the location, a description of what occurred, a sketch of the accident site, the victims´ age, travel modes, and the type of injuries incurred.

The quality of the data in STRADA varies, depending on whether both police and hospital report are available (either might be missing). Police reports are generally more reliable regarding accident location and the description of what occurred, while hospital report are much more reliable regarding injury severity. This means that the most reliable information is available when both police and hospital reports are available for given accident. But focusing only on cases for which both reports are available would introduce bias into the analysis, since many accidents would be excluded. Only 33% of the collisions between a motorized vehicle and a pedestrian or a bicyclist registered in STRADA[1] for 2013 are attested by both a police report and a hospital report.

It should also be obvious that not all traffic accidents are registered in STRADA (or in any accident database, for that matter). If no one was injured, and if there was no property damage, it is likely that the accident would not be reported to the police and

[1] In the year 2013 there were 3 738 registered injured persons from collisions between motorized vehicle and pedestrian or bicyclist in STRADA. Of those, 1 225 (33%) included police and hospital reports, 1 544 (41%) included only police report and 969 (26%) included only hospital report.

that no one would visit the hospital. Those accidents are missing from the accident database (underreporting); hence, they cannot be included in any analysis that is based on the accident database. Hence, the *reporting degree* (i.e. the proportion of accidents that are registered) varies. Reporting degree also varies across transport modes, countries and injury severity/outcome (Elvik and Mysen, 1999, Jonsson et al., 2011).

1.1.1 Pedestrian and bicyclist accidents

In order to understand the importance of accidents involving pedestrians and bicyclists, it is necessary to relate the situation for those groups to the accident situation in general. In 2013, STRADA registered 53 332 individuals as having been involved in accident and injured. Of those, 30% were pedestrians and 23% were bicyclists and the share of pedestrians and bicyclists grew smaller as the injuries became more serious[2] (i.e. the overall probability of serious or fatal injuries was lower for pedestrians and bicyclists compared to all accidents), see figure 1. Observe that those proportions might be influenced by high levels of underreporting for pedestrian and bicyclist accident and that the reporting degree may vary between accident types (Elvik and Mysen, 1999).

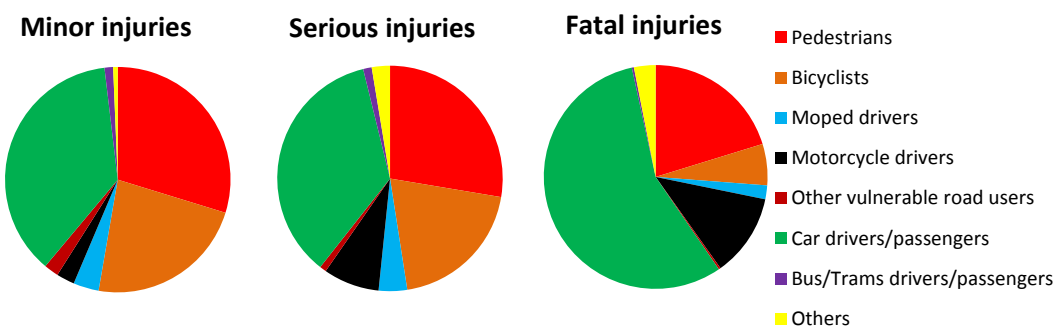

Figure 1: The distribution of registered accidents among different transport modes by injury severity/outcome. Based on injury accidents, registered in STRADA year 2013 (*n=53 332*).

[2] The definition of serious injury was ISS9+, or according to the police report if no hospital report was available. The ISS scale is explained in section (1.1.3).

Accidents involving pedestrians and bicyclists can be divided roughly into nine groups:

(1) Single pedestrian accidents

(2) Single bicyclist accidents

(3) Collisions between pedestrians and bicyclists

(4) Collisions between two or more bicyclists

(5) Collisions between pedestrians and mopeds

(6) Collisions between bicyclists and mopeds

(7) Collisions between motorized vehicles and pedestrians

(8) Collisions between motorized vehicles and bicyclists

(9) Others

Figure 2 shows the accidents involving pedestrians or bicyclists by accident type and injury severity/outcome. The majority of the accidents are single accidents. The accidents involving motorized vehicles, however, become more dominant as the injuries become more serious. These data clearly shows that accidents involving motorized vehicles have a greater probability of resulting in serious or fatal injuries than other accident types do (observe, however, that this trend might be influenced by reporting degree). This finding aligns with previous research, which has shown that accidents involving motorized vehicles account for most accidents that are fatal for bicyclists (e.g. Chong et al., 2010, Scheiman et al., 2010) and the probability of serious or severe injury is higher in collisions that involve motorized vehicles than it is for single accidents involving only pedestrians (Öberg, 2011) or bicyclists (Langley et al., 2003, Sze et al., 2011).

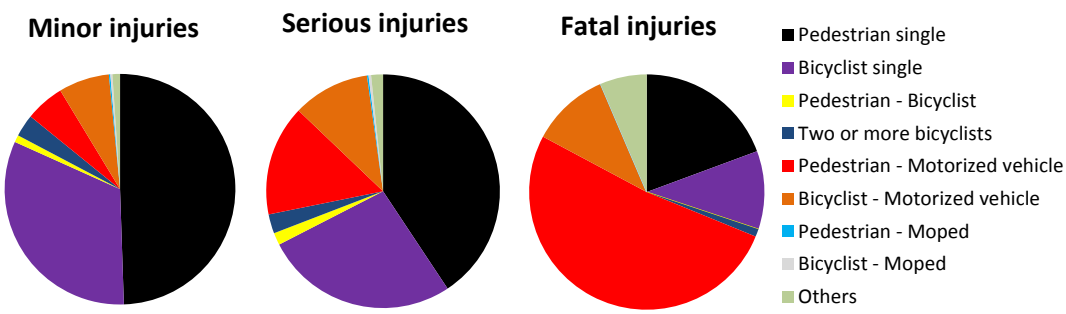

Figure 2: The distribution of accident types involving pedestrian and bicyclists by injury severity/outcome. Based on accidents, involving injuries registered in STRADA for 2013 (*n=27 881)*.

1.1.2 Age and accidents involving pedestrians and/or bicyclists struck by motorized vehicles

Age has frequently been shown to influence accident statistics in terms of both the risk of becoming involved in an accident (e.g. Gustafsson and Thulin, 2003) and the injury severity/outcome of those accidents (e.g. Eluru et al., 2008, Henary et al., 2006). Figures 3 and 4 show the injury severity/outcome by age groups for pedestrians and bicyclists struck by motorized vehicles. The data shows that the older age groups are overrepresented in serious and fatal injuries, both for struck pedestrians and struck bicyclists, i.e. seniors are more likely to be seriously injured or to die as a result of traffic accidents. It is also interesting that this overrepresentation of the age group 65 and older is much greater for bicyclists than it is for pedestrians.

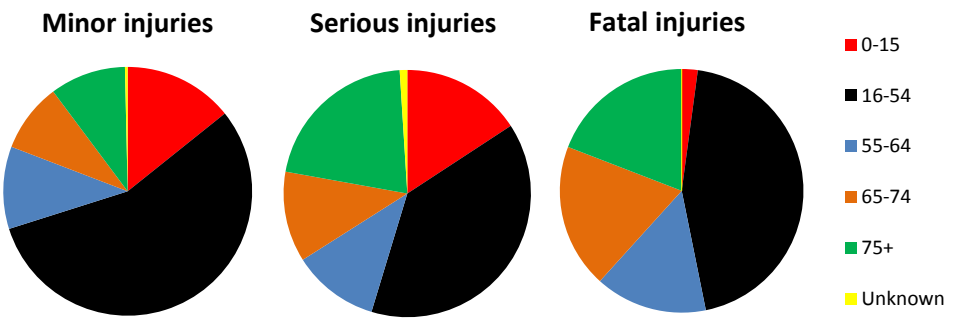

Figure 3: The distribution of age groups by injury severity/outcomes for pedestrians struck by motorized vehicles. Based on injury accidents, registered in STRADA for 2013 (*n=1 689)*.

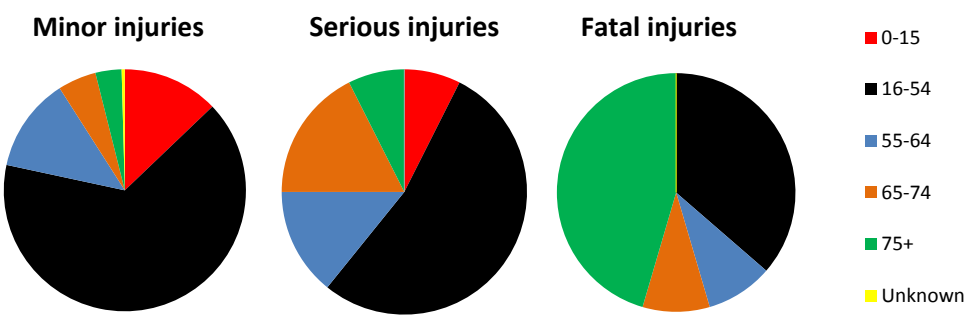

Figure 4: The distribution of age groups by injury severity/outcome for bicyclists struck by motorized vehicles. Based on injury accidents, registered in STRADA for 2013 (*n=2 049)*.

1.1.3 Defining injury severity

In order to analyze accidents involving serious injuries, one must first define what a serious injury is. Injury severity is often estimated in one of two ways, depending on the availability of data:

(a) Hospital report typically includes estimate called *Abbreviated Injury Scale (AIS)* and the *Injury Severity Score (ISS)*. These values are frequently applied in traffic accident analysis, even though injury severity can be coded using other scales, such as the Glasgow Coma Scale, the New-ISS (NISS), the International Classification of Injuries Severity System (ICISS), and the Head Injury Criterion (HIC) (Liu and Yang, 2003, Seguí-Gómez and Lopez-Valdes, 2012).

To determine the AIS value, the body is divided into eight body regions: head, face, neck, thorax, abdomen, spine, upper extremities and lower extremities (it is also possible to code the body region of the injury as unspecified). To determine the seriousness of the injury, the Association for the Advancement of Automotive Medicine (AAAM), which is responsible for the AIS scale (Seguí-Gómez and Lopez-Valdes, 2012), has created a list of possible injuries and assigned a specific AIS value between 0 and 6, representing the injury´s severity, to each of those injury types; 1 is a mild injury and 6 is maximum (virtually un-survivable)[3]. If a certain injury is registered in the hospital report, the corresponding AIS value is assigned to the body region that sustained the injury. It is possible to register multiple injuries in a single body region, and each region is usually summarized in terms of the highest AIS value recorded for that body region. To obtain a more general estimation of the seriousness of a person´s combined injuries, the scale defines one *Max AIS value (MAIS),* which is the highest AIS value registered in any body region.

The seriousness of an injury may be influenced by that there are multiple injuries. A combination of AIS3 and AIS2 injuries might be more serious than a single AIS3 injury, for instance, even though both would be registered as MAIS3 injury. The ISS scale is used to consider that there are multiple injuries. The ISS scale is a derivative of the AIS scale, and it uses the three body regions with the highest AIS value to calculate the ISS value (exception is that if an AIS6 injury is registered, then the ISS is registered as 75); see equation 1.

$$\textit{Equation 1:} \qquad ISS = AIS_1^2 + AIS_2^2 + AIS_3^2$$

The definition of serious injury (according to the AIS and ISS scale) varies somewhat, depending on the aim of the work. Usually AIS3+ (AIS3 or higher) is considered a

[3] AIS0: No injury, AIS1: Minor injury, AIS2: Moderate injury, AIS3: Serious injury, AIS4: Severe injury, AIS5: Critical injury, AIS6: Maximum injury, virtually un-survivable (Seguí-Gómez and Lopez-Valdes, 2012).

threshold for categorizing injuries as serious[3]. Observe, however, that the AIS value is 'independent' of the outcome (the AIS value does not consider the individual´s preconditions that can influence the probability of survival; there is, though, a strong relation between the AIS scale and the risk of fatality), an AIS1 injury can be fatal (Seguí-Gómez and Lopez-Valdes, 2012). The threshold for the ISS scale varies more[4]. Many (e.g. Stevenson et al., 2001), including the Swedish Transport Administration, use ISS9+ as the threshold for serious injuries; however, others have suggested that higher values are in order if the focus is to be more on the risk of fatality than on the morbidity (Palmer, 2007).

(b) The second way to determine an injury´s severity from accident databases is to use the estimation given in the police report, i.e. the assessment of the officers on site. This estimation can differ from that of the hospital report, which is far more reliable; however, since hospital reports are often not available it is sometimes necessary to use this estimate.

1.2 Exposure, risk and consequence

The traffic is constantly changing; therefore it can be difficult to draw any conclusions from raw accident statistics. To better understand the importance of various factors for the number and injury severities of the accidents, it can be helpfull to divide the problem into the dimensions *exposure, risk* and *consequence* (Nilsson, 2004). Exposure is how much travelling there is, or the number of events that can result in an accident; risk is the probability of one´s being involved in an accident per unit of exposure (risk per travelled kilometer, per road user, per interaction etc.) and consequence is the probability of a certain injury degree, given that a person is involved in an accident. The advantages of this kind of approach are best described by a hypothetical example:

> *"The number of seriously injured bicyclists is reduced by 20% between two years, after major traffic policy changes."*

What does this mean? The reduction, itself, does not say much about what has occurred or how this seemingly safety improvement was achieved. It is possible that the reduction in number of accidents was simply due to that people cycle less, i.e. the number of accidents has fallen (or perhaps migrated to another road user group, which would entail no overall reduction in the number of serious injuries), but the

[4] ISS1-3: Minor injury, ISS4-8: Moderate injury, ISS9-15: Serious injury, ISS16-24: Severe injury, ISS25-75: Critical injury (Stevenson et al., 2007)

risk per cyclist remained the same. It can be debated whether such a scenario should be seen as safety improvement, where both answers have their merits. Now consider a case in which it is known that the exposure was not influenced by this policy change and has not changed. In such a case it is possible to state that the safety has improved. But why did the number of serious injuries decline? It is possible that the number of accidents was reduced, i.e. that this was an active safety change (a change that prevents accidents); or perhaps the measure lowered the probability that bicyclists would be seriously injured if involved in an accident, i.e. a change in passive safety (a change that reduces the consequence if one is involved in an accident). It is also possible that the change influenced both dimensions simultaneously in the same, or the opposite, direction. Without dividing the data into these three dimensions it can be difficult to understand how multiple factors influence the number of injuries, making it challenging to avoid misinterpretations that might be counterproductive in the efforts to improve road safety.

1.2.1 Relations between the dimensions

Multiplying exposure by risk yields the number of accidents. There is, on one hand (for example) the number of travelled kilometers and on the other the risk of being involved in an accident per driven kilometer, hence the number of accidents, see equation 2. Including the consequence dimension in this multiplications provides the number of accidents multiplied by the probability of a given injury severity per accident, and hence the number of injuries of given injury severity/outcome, see equation 3. It is therefore straight forward that all three dimensions should influence the number of serious and fatal injuries.

Equation 2 $\quad Number\ of\ accidents = Exposure \cdot Risk$

Equation 3 $\quad Number\ of\ injuries = Exposure \cdot Risk \cdot Consequence$

In addition, there is a complex, partially unknown, interdependency between the three dimensions, see figure 5, i.e. exposure, risk and consequence are not independent of each other. In order to understand the accident data and the relations they represents, it is necessary to understand this interdependency. Describe this interdependency, requires two additional concepts: (a) *Behavior*, which here refers to actions such as modal choice, route choice, speed choices, gap acceptance, driving under influence of alcohol, fatigue etc.; and (b) *subjective safety*, which is perceived or felt safety (compared to *objective safety*, which is the 'recordable' traffic safety, i.e. number of accidents, the actual risk of an accident and the consequences of those accidents, hence exposure, risk and consequence dimensions).

Several studies have found a non-linear relation between exposure and risk (e.g. Ekman, 1996, Jacobsen, 2003, Jonsson, 2005). However, the fact that this relation is non-linear indicates that this effect is a result of a more complex underlying relation.

This has frequently been related to that higher exposure results in greater awareness among road users of each others and that exposure influences their subjective safety, resulting in behavior changing (e.g. Brüde and Larsson, 1993, Ekman, 1996). Hence, that exposure influences behaviour and subjective safety, see figure 5. It is also logical that subjective safety (i.e. perceived safety), which is influenced by (among other things) exposure, will influence behavior (Wilde, 1982), and/or that behavior is influenced by some combination of subjective safety, task difficulty and drivers capability (Fuller, 2005).

It is logical that objective safety, both risk, consequence and exposure, will influence subjective safety, even though the relation is not a perfect one. In addition, again, subjective safety is believed to influence the behavior of road users. Several behaviors have been shown to influence the risk of an accident occurring, e.g. driving while under the influence of alcohol or drugs (Gjerde et al., 2011, McLean et al., 1980), fatigue (Komada et al., 2013), and choice of speed (McLean et al., 1994). Behaviour can also influence the consequence, e.g. speed choice (e.g. Leaf and Preusser, 1999, Pasanen and Rosén, 2010) which influences the *impact speed* (i.e. the speed of the vehicle in the moment of collision) which is strongly related to the probability of fatality (e.g. Richards, 2010, Rosén et al., 2011), and, hence to the consequence. This circular relation, *objective safety - subjective safety - behavior - objective safety*, in which a change in objective safety can cause behavioral changes that in turn can affect objective safety, is a phenomenon often referred to as *behavioral adaptation* or *risk compensation* (Wilde, 2014).

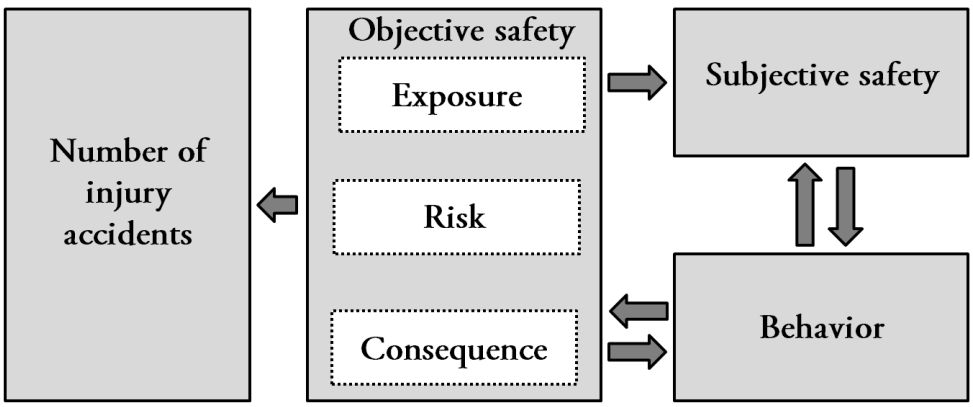

Figure 5: A simplified description of the relation between the number of accidents of different injury severities, exposure, risk and consequence (objective safety), subjective safety and behavior.

It therefore seems clear that these three dimensions are interrelated through, (among other factors) road user behavior and subjective safety, and that the two sided relation between behavior and subjective safety is an important link to understanding the relations between exposure, risk and consequence. It is, however, sometimes difficult to analyze those sub-relations (i.e. the role of behavior and subjective safety). Therefore the relations between the dimensions *exposure - risk - consequence* are, in

traffic accident analysis, often investigated ´directly´, for example the relation between exposure and risk (e.g. Jacobsen, 2003). Deeper discussion regarding the underlying psychological processes behind those relations can be found in the vast literature on traffic behavior (e.g. Fuller, 2005, Näätänen and Summala, 1974, Ranney, 1994).

1.2.2 The relation between exposure and risk

The relation between exposure and risk is one of the most discussed of the interdependencies between the three dimensions, often described using what is called a *safety performance functions*, which is a mathematical model that aims to describe the number of accidents as a function of exposure (of different road user groups) and other variables. Those models most often have the form shown in equation 4 (Elvik and Bjørnskau, 2014), where N is the number of accidents, E_i is the exposure of different road user groups, E_k are various variables that describe the environment (*geometric variables*) and β_i and β_k are constants.

Equation 4: $$N = Exp(\beta_0) \prod E_i^{\beta_i} \cdot e^{\sum E_k \beta_k}$$

Earlier studies have shown this relation to be non-linear for pedestrians and bicyclists struck by motorized vehicles (e.g. Brüde and Larsson, 1993, Elvik, 2009a, Jonsson, 2005, Leden, 2002), where the exponent is frequently between 0.3 and 0.7 for the volume of pedestrians and bicyclists and frequently between 0.4 and 0.8 for flow of motorized vehicles (Elvik, 2009a). This suggests that the number of accidents does not increase proportionally as fast as the proportional increase in number of pedestrians and bicyclists. This phenomenon is frequently referred to as *safety in numbers*. The models further show that the numbers of accidents, and hence, the risk of accident per vulnerable road user, increases with an increase in the flow of motorized vehicles (e.g. Brüde and Larsson, 1993, Elvik, 2009a, Jonsson, 2005). Hence, the number of accidents is a combined effect of the exposure of all the road user groups involved.

There is a logical reason why the number of accidents can be expected to change with the exposure. Each occurrence or action has a given probability of resulting in an accident; therefore, if more pedestrians or bicyclists are present, the probability that something will go wrong somewhere increases. Also, for collision to occur requires interaction between two or more road users, and since the number of interactions is related to the number of road users (i.e. exposure; Elvik et al., 2009); logic dictates that there should be a relation between them. The fact that the relation seems to be non-linear requires some discussion. The literature identifies at least five potential explanations for this:

(a) *Behavioral adaptation:* The presence of more pedestrians and/or bicyclists makes car drivers more aware of them; the car drivers therefore adjust their

behavior, resulting in safer traffic environment for pedestrians and bicyclists (e.g. Brüde and Larsson, 1993, Ekman, 1996, Jacobsen, 2003).

(b) *Learning process:* Travelling more often as pedestrian or a cyclist would possibly result in each and every individual being exposed to conflicts, allowing him or her to learn from those and become more skilled at travelling safely (Elvik, 2014a, 2015, Phillips et al., 2011).

(c) *Infrastructure and maintenance quality:* It is possible that municipalities make extra efforts to create safe infrastructure if the exposure is high, this would create a correlative relation, in which high exposure locations would be safer, which might cause this statistical relation (e.g. Brüde and Larsson, 1993, Jonsson, 2013, Schepers, 2012).

(d) *Spurious correlation:* This might partly be a statistical phenomenon. If the model is based on ratio variables, i.e. the dependent variable is A/B and the independent variable is B. If a randomly generated data (i.e. the number of accidents (A) and the exposure (B) is randomly generated independently of each other) is used to estimate a model for risk per road user (A/B) that can automatically result in hyperbolic relation i.e. lower risk per road user as the exposure increases (Brindle, 1994, Elvik, 2013a). Elvik (2013a) concluded that model on the form in equation 4 is not as sensitive to this effect.

(e) *Numbers by safety:* It is possible that the relation is reversed and that this is not a causal relation; that pedestrians and bicyclists choose to travel in locations that are perceived as safe (Bhatia and Wier, 2011).

It is important to realize that even though a safety performance function identifies a statistically significant relation, that does not automatically mean that there is a causal relation, i.e. higher exposure does not inevitably result in lower risk (Kulmala, 1995). For example, infrastructure quality probably correlates with the exposure, but increasing the exposure will not automatically improve the quality of the infrastructure, hence, that causal effect will not be apparent.

1.2.3 The influence of the speed environment on objective safety

The speed of motorized vehicles transcends all the three dimensions; however, the way of influence of the specific dimension depends on what is referred to as speed. There are several different speed variables, that each influence objective safety (and for that matter the subjective safety as well) in its own way; they need to be related to exposure, risk and consequence, see figure 6.

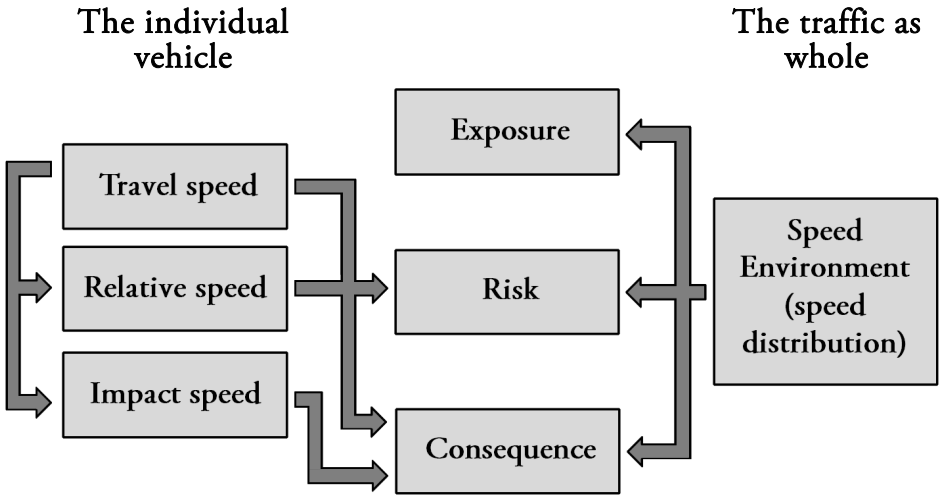

Figure 6: A schematic describing how different speed concepts for the individual vehicle and the traffic as a whole influence the exposure, risk and consequence.

Let us start by focusing on the speed of the traffic as a whole, i.e. the speed environment. The speed environment influences subjective traffic safety (Kaufmann et al., 2005) and the travel time of different travel modes; hence, speed might influence the modal choice and route choice of the road users, i.e. there is a relation between exposure and the speed distribution of the traffic as a whole.

Mean travel speed has frequently been related to the risk of an accident occurring and to the consequences of that accidents (mean travel speed being the mean speed of a vehicle passing through a given point in space). The power model and the exponent models (Elvik, 2009b, Harkey et al., 2008) demonstrate that an increase or a decrease in mean travel speed influences the number of accidents, and the influence is greater on the more serious accidents (Elvik, 2009b, Nilsson, 2004), hence, mean travel speed is related to both the risk and the consequence dimension. However, to our knowledge, none of those models are calibrated for pedestrian and bicyclist accidents (Elvik, 2009b). It is debatable whether models based on motorized vehicle accidents are suitable basis to understand relations regarding accidents involving pedestrians and bicyclists. There are some differences how those groups interact with the motorized traffic compared to how motorized vehicles interact with one another. Pasanen (1992) created a theoretical model based on mathematical modelling in order to investigate how (among other things) changes in travel speed would influence the probability of a fatal accident occurring. These models suggest that driving at 65 km/h increases the probability of fatality by a factor of 2.5, compared to driving at 50 km/h.

Speed variation has been shown to have relation with the risk of an accident occurring (Garber and Gadirau, 1988). Earlier research has shown drivers who drive slower or

faster than the average driver to have elevated risk of accident involvement (e.g. Solomon, 1964); however Kloeden et al. (1997) pointed out some methodological limitations in the earlier studies that might have biased the results. Kloeden et al. (1997) showed that the relative risk of accident involvement, where ambulance was required, was elevated for vehicles that had higher speed compared to control vehicles, while they could not show any tendency in accident risk for vehicles driving more slowly than the control vehicles. Newer studies have used high resolution data (i.e. where the speed and speed variation are collected preemptively so that the situation at the time of the accident can be examined) to study this relation and have shown that speed variation influences the accident risk (Zheng et al., 2010). However, since variation in speed can be correlated with the overall mean travel speed (Elvik, 2014b), it can be difficult to determine whether the influence on accident risk results from the speed variation or simply from correlation with the mean travel speed (and vice versa: some studies have shown the speed variation to be statistically significant to the risk of an accident occurring, while the mean travel speed was not statistically significant (Quddus, 2013). Given the amount of evidence from, among other, before and after studies (e.g. Elvik, 2005, Elvik, 2009b), it is unlikely that the importance of mean travel speed owes only to correlation). In order to try to circumvent this problem, Elvik (2014b) tried to fit the results of four studies to the variation coefficient instead of to the variance in speed distribution (the variation coefficient is the standard variation of speed divided by the mean travel speed). All the data showed that there is some relation between the variation coefficient and the accident risk, even though the results varied considerably. Elvik (2014b) concluded from a literature review that higher variation in speed increases the accident risk, however, that the degree of influence varies considerable between studies. Finally, Taylor et al. (2000) suggested that even the proportion of drivers that are driving faster than some threshold (compared to mean travel speed or speed limit) is also important for the accident risk.

There are some logical explanations for why speed distribution might in some cases be important to accident risk. A driver who is not travelling at mean speed is likely to interact more frequently with other vehicles; also, if a vehicle is travelling at a higher speed (resulting in higher speed variation), this would increase the *reaction distance* for that driver (McLean et al., 1994), i.e. the distance travelled between the moment the driver discovers a possible risk of an accident and the moment he or she reacts to this risk. Hence, there is some logical and empirical support for the idea that speed variation might influence (or at least correlates with) the risk dimension. Given that higher speed variation allows for a higher speed of the vehicle that might be involved in an accident, it can be vaguely argued that there is also a logical relation between speed variation and the consequence dimension. Like the studies based on mean travel speed, however, these also consider only accidents involving motorized vehicles, and again, it can be debated how this influence would differ for the accident risk for pedestrians and bicyclists.

The speed of traffic as a whole is not directly related to the accidents, i.e. its relation to risk and consequence is not fully causal. A higher mean travel speed does not automatically result in an increased risk for all drivers, nor does it necessarily result in more serious consequences. This relation is probabilistic, rather than causal. If some or all vehicles are driving at higher speeds (resulting in a higher mean travel speed or greater speed variation), the probability that each vehicle (at least those that are moving faster) will be involved in an accident is higher (for one thing, because the reaction distance is longer), i.e. there is a probabilistic relation: *Mean travel speed ~ travel speed of an individual vehicle ~ risk that the individual vehicle will be involved in an accident*. Because of this probabilistic relation between the speed factors of traffic as a whole and the travel speed of the individual vehicle, it stands to reason that the speed of traffic as a whole will also have a probabilistic relation to the impact speed of the individual vehicle involved in an accident; but the impact speed has been shown to have a strong relation to the injury severity/outcome (e.g. Richards, 2010, Rosén, 2013, Rosén and Sander, 2009, Tefft, 2013). Therefore, the mean traffic speed of traffic as a whole has a probabilistic relation to the risk and consequence dimension.

The speed of the individual vehicle has a much more direct relation to the risk and consequence dimensions, a more causal relation. It is always an individual vehicle, not the traffic as a whole, that is involved in a traffic conflict (a traffic conflict being a situation, in which an accident will occur if no one takes evasive action) or an accident. The travel speed of a motorized vehicle, that is potentially involved in a collision, will influence how long the reaction distance is, thereby the potential for the driver to avoid the accident, hence the risk of an accident occurring (McLean et al., 1994). There is also a strong relation between travel speed and impact speed, since from the moment the driver starts to brake; the deceleration is controlled by physical laws that are influenced by the initial speed. The impact speed (and in the case of accidents only involving motorized vehicle the change in speed) of the vehicle involved in an accident controls the forces the victim is subjected to. This is in essence a physical relation that has been shown to have a strong relation in all types of accidents involving motorized vehicles: accidents involving only motorized vehicles (Richards, 2010), collisions between motorized vehicles and pedestrians (e.g. Rosén and Sander, 2009, Tefft, 2011), and collisions between motorized vehicles and bicyclists (Rosén, 2013). Hence, travel speed is related to the risk and consequence dimensions and impact speed is related to the consequence dimension.

Some studies have shown relations between the speed of the individual vehicle relative to the speed of other vehicles and the risk of being involved in an accident (Kloeden et al., 1997). Similarly, as with the traffic as a whole, there might be a vague logical relation between the relative speed of the individual vehicle and the consequences of the accident: a higher relative travel speed would ultimately result in a higher impact speed, and hence in more severe injuries.

To sum up, the speed of the individual vehicle has a strong direct relation to the risk and consequence dimensions, while the speed of traffic as a whole has a probabilistic

relation to the speed of all the individual vehicles, including those that are involved in an accident, and hence to the risk and consequence dimension. However, traffic speed also relates to the exposure dimension.

Earlier research has found that several factors are related to the speed choice for motorized vehicles. Among these are (a) the infrastructure, e.g. the road geometry (Berntman et al., 2012), road surface (Ihs and Velin, 2002), speed limit (Hydén et al., 2008, Sagberg, 2005); (b) the vehicle properties, e.g. model year (Wasielewski, 1984, Yusuf, 2010), engine capacity (Quimby et al., 1999) and vehicle type (Rudin-Brown, 2004); (c) individual factors, e.g. drivers age (Wasielewski, 1984, Yusuf, 2010, Sagberg, 2005), number of passengers (Yusuf, 2010, Wasielewski, 1984), gender (Quimby et al., 1999), psychological and emotional state (Danaf et al., 2015), attitude (Haglund and Åberg, 2000), perceived risk (Sagberg, 2005) and driving milage, i.e. how many kilometers driven per year (Quimby et al., 1999); (d) temporal factors, e.g. weather and road conditions (Yusuf, 2010), time of day or year (Wallman, 2005); and (e) other road users (Várhelyi, 1998), see figure 7. Observe that this not a complete list, only a sample of the factors that influence the speed choice.

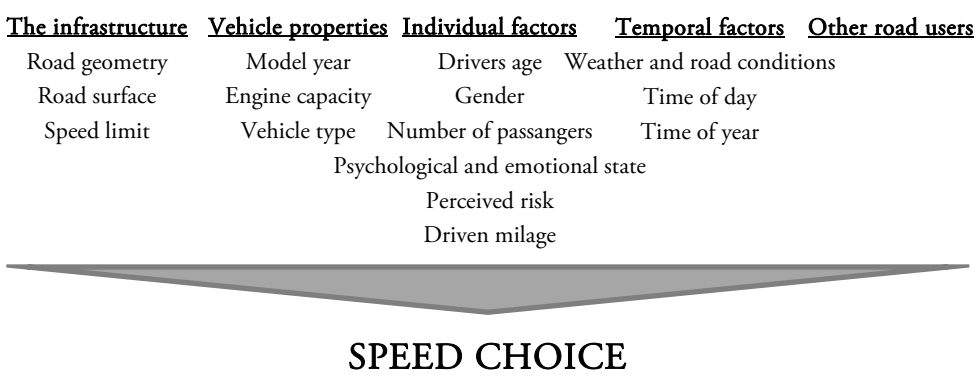

Figure 7: Influential factors for the choice of travel speed.

The number of accidents results from a combination of the three dimensions (which are themselves influenced by many factors). This creates a unique relation between the number of accidents and the speed environment. In 2013, 713 collisions between motorized vehicles and pedestrians and 938 collisions between motorized vehicles and bicyclists were registered in STRADA, where the speed limit was also registered[5]. The data show that the great majority of the accidents occurred in areas where the speed

[5] 42.2% of the accidents registered in STRADA for 2013 between motorized vehicles and pedestrians included the speed limit at the accident site, the figure for accidents between motorized vehicles and bicyclists was 45.8%.

limit was 20-50 km/h, however, where the speed limit was higher, the proportion of serious injuries and/or fatalities is also higher; i.e. serious and fatal accidents are overrepresented in high speed environments, see figures 8 and 9 (but observe that the distribution of injury severity/outcome is even more biased for accidents with registered speed limits than in the database as a whole, owing to underreporting). This is a combined influence of the three dimensions discussed earlier, where the exposure of pedestrians and bicyclists occurs mainly within urban areas in 20-50 km/h environments, while at higher speeds they are segregated from the car traffic, thereby lowering the risk of an accident occurring (or lowering exposure, if exposure is defined as interactions). The reason for the overrepresentation of high speed environments among serious and/or fatal injury accidents can probably be attributed to increased probability of serious or fatal injuries in high speed environments (Leaf and Preussure, 1999, Tefft, 2011).

The most common Swedish speed policy for urban settings is to use a speed limit of 50 km/h generally and one of 30 km/h in sensitive areas, tough the speed limits of 20 and 40 km/h were recently introduced. Since travel speed heavily influences the probability of an accident (Nilsson, 2004) and the injury severity/outcome if involved

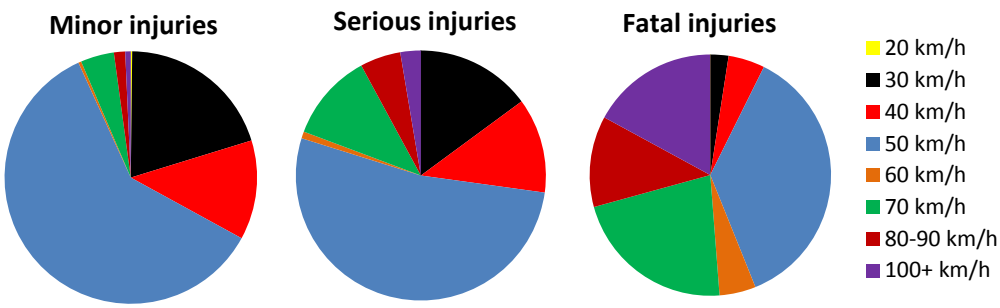

Figure 8: The distribution of accidents between pedestrians and motorized vehicles by speed limits and injury severity/outcome. Based on accidents registered in STRADA for the year 2013 (*n=713*).

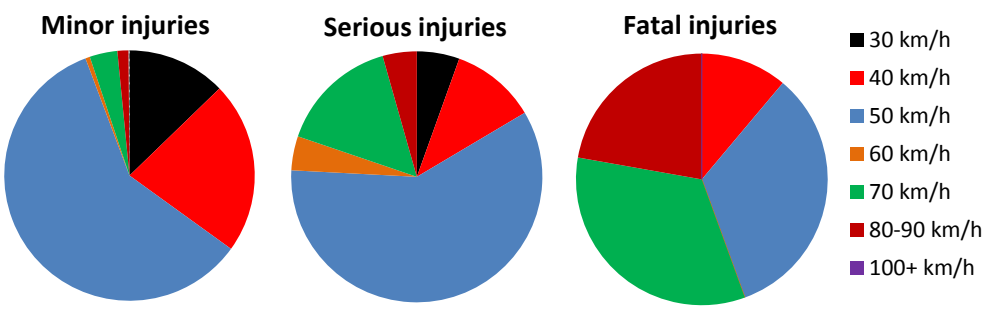

Figure 9: The distribution of accidents between bicyclists and motorized vehicles by speed limits and injury severity/outcome. Based on accidents registered in STRADA for the year 2013 (*n=938*).

in an accident (Pasanena and Rosén, 2010), it is not surprising that previous studies have shown that the probability of serious and/or fatality is higher when the speed limits is higher (Eluru et al., 2008, Gårder, 2004, Kaplan, 2014, Leaf and Preusser, 1999, Sze and Wong, 2007), even though this finding might be influenced by confounding factors. The speed policy, speed limits and changes there of also have potential as powerful tool for influencing traffic safety (Islam and El-Basyouny, 2015, Taylor et al., 2000). A speed limit reduction from 60 to 50 km/h in Zürich, Switzerland, resulted in a 20% decrease in pedestrian injuries and an 80% decrease in AIS5+ injuries (Walz et al., 1986). At the same time, a speed limit reduction in Denmark from 60 to 50 km/h resulted in only minor change in number of injury accidents which was not statistically significant (Fridstrøm et al., 1995).

The actual speed limit, however, is only one of many factors that influence speed choices; hence, changes in speed limits will have only a limited effect on actual travel speeds and mean travel speeds. Speed limit changes of 10 km/h frequently resulted in between 0 and 7 km/h changes (in several cases the change in mean travel speed was in the opposite direction compared to the change in speed limit) in mean travel speed (Bång and Pezo-Silvano, 2012, Hydén et al., 2008, Islam et al., 2014). It can also be debated whether the mean travel speed is the best estimator, given that perhaps high speed drivers constitute the biggest safety issue.

When considering speed policy and changes to it, one must consider that the speed policy has an extensive influence on the society in terms of travel time, environmental effects, mobility and accessibility, the interaction between road user groups, and travel mode. Some effects are positive while other are negative; therefore, when deciding on speed policy, one must consider the costs and benefits of the proposed changes, the different influences of those changes, and how realistic it is to enforce the new speed limits.

1.3 The accident process

Now, when we have established the grand scope of things, let us focus on the accident process, i.e. the events that occur from the point of traffic conflict to the consequences. The process leading up to an accident and the accident itself can be divided into three phases:

(1) Pre-collision and normal driving **Risk**

(2) The collision **Consequence**

(3) Post-collision

The first phase spans everything from normal driving until a collision occurs or the traffic conflict is resolved without an accident. This phase can be described using the exposure and risk dimensions. The second phase is the collision itself, i.e. what impacts occur and which injuries are sustained. The third phase is the aftermaths, i.e. what occurs after everything has come to a stop.[6] The victim might receive help in time or he or she might not; he or she might recover, survive or perhaps die from the injuries. Those two phases fall within the consequence dimension.

1.3.1 Pre-collision: The risk of an accident

Numerous factors have been shown to influence the risk of an accident occurring, e.g. age (Blaizot et al., 2013, Hollingworth et al., 2015, Jonah and Engel, 1983, Rodgers, 1995, Xiang et al., 2006), gender (Hollingworth et al., 2015, Rodgers, 1995, Xiang et al., 2006), cycling experience (Hollingworth et al., 2015), even disabilities, however, that study did not control for exposure (Xiang et al., 2006), behavior (Hollingworth et al., 2015), the infrastructure (Ekman, 1996, Hollingworth et al., 2015), but the infrastructure has great potential to influence road users´ behavior, visibility, awareness and the need for interaction (collisions occur only after some kind of interaction between two or more road users). Temporal environmental factors, such as daylight have also been shown to relate to the risk of an accident (Rodgers, 1995), as has exposure (e.g. Jacobsen, 2003, Jonsson, 2005). Of course, this list is not complete, since thousands of factors can influence the accident risk.

If we turn our attention towards the importance of speed to accident risk, in traffic, the road user must be aware of what is going on, make decisions, and react to prevent a collision or to mitigate the consequences. The reaction time can vary (reaction time being the time between the moment the driver sees something and the moment he or she takes some action), and during this time, the vehicle will continue to travel at the initial speed (the travel speed); that is, during the reaction time, the vehicle maintains its original speed. If at the moment the driver realizes there is a potential conflict, the distance to the collision point is shorter than the reaction distance, the impact speed will be equal to the travel speed. If the distance to the collision point is longer, the road user might manage to take some mitigating actions, resulting in a lower impact speed or avoiding the accident altogether.

Several individual factors have been shown to influence the reaction time, such as age, driving under the influence of alcohol, cognitive load, urgency, a driver´s expectations

[6] Some authors suggest different phases, for example, Hannawald and Kauer (2004) defined ground impacts and the injuries sustained from such impact as the post collision phase.

(Christoforou et al., 2013, Green, 2000, Makishita and Matsunaga, 2008). Those factors are therefore likely to influence the risk of an accident occurring.

Studies have shown that in collisions between motorized vehicles and pedestrians, the driver manages to brake or to take other evasive actions in about half of the accidents (Anderson et al., 1997, Cuerden et al., 2007, Isenberg, 1998). One study showed a lower proportion (Falkenberg, 2008), in which braking occurred in only one third of the accidents (and even lower proportion of the bicycle accidents), and another (Ahston, 1978) showed that a far greater proportion managed to brake. The difference in Falkenberg (2008) might possibly be explained by the fact that the possibility of other evasive maneuvers was not included in that study. No explanation was found for the differences in the data used by Ahston (1978), but that study is much older and that might affect its results. Travel speed is therefore important in determining whether a collision will occur (the risk dimension); this relation has been identified in earlier studies (Elvik, 2009b, Nilsson, 2004), even though those studies were not concentrated on pedestrian and bicyclist accidents. Therefore, all the factors listed in figure 7 that have been shown to influence speed choice can be expected to influence the risk of an accident occurring. Moreover, a single factor can affect several influential factors simultaneously.. For example, an older age might result in lower travel speeds (Sagberg, 2005) which alone reduces the risk of an accident´s occurring; however, at the same time, higher age might increase the driver´s reaction time (Makishita and Matsunaga, 2008), which will counteract the influence of the speed change.

1.3.2 The collision, post collision, and injury severity/outcome

Figure 10 presents a schema covering the different phases in the collision and post collision phases, as well as the most influential factors affecting the injury severity/outcome. This section explains and discusses those relations, along with current knowledge about them.

There is a extensive literature available regarding what occurs when a pedestrian is struck by a motorized vehicle. Much less is known about accidents between motorized vehicles and bicyclists. The sections therefore start by discussing the accident process from the perspective of a pedestrian struck by motorized vehicle.

Accident mechanisms

In this work, *accident mechanisms* refers to the movements, contacts and impacts that occur during a collision and to the forces of those impacts, namely, where the pedestrian comes into contact with the motorized vehicle and the ground, the parts of the body are exposed to violence or impact, and the factors influencing these mechanisms. Accident mechanisms are complex in collisions between a pedestrian and a motorized vehicle; there may be multiple contacts between the victim, the

vehicle, and the ground, and each contact has the potential to cause an injury. This process is influenced by many factors, such as the impact speed of the vehicle (Nie and Yang, 2014, Walz et al., 1986), characteristics of the pedestrian (Wood et al., 2005) and the physical characteristics of the vehicle (Wood et al., 2005). Accident mechanisms can be roughly be divided into five different types: (a) fender vault, (b) wrap projection, (c) forwards projection, (d) run over accidents and (e) reverse accidents.

A fender vault occurs when the pedestrian (or the bicyclist) is struck by the side (or front) of the vehicle, however, the victim is thrown to the side without any impact having occurred between the person´s upper part and the vehicle (Wood et al., 2005).

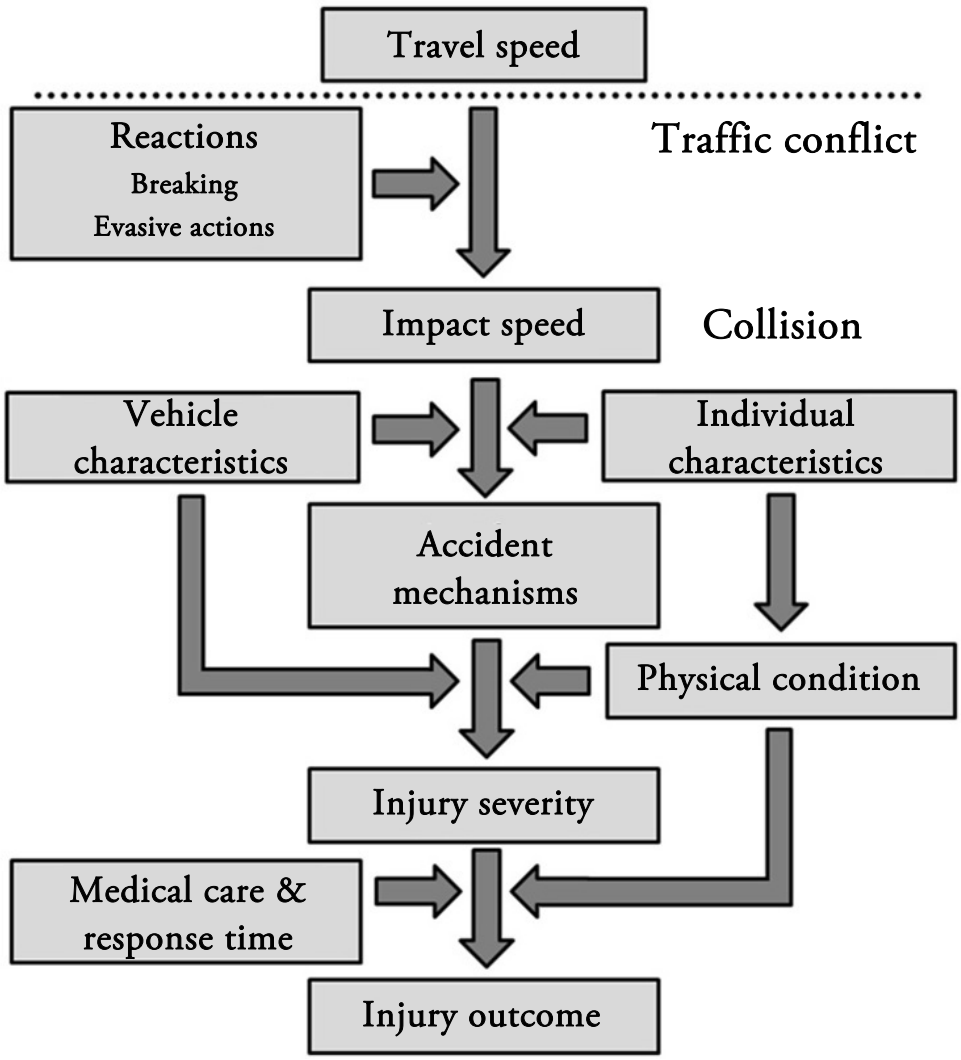

Figure 10: Overview of the phases of an accident and the accident mechanisms.

This accident type is frequently excluded from studies of collisions involving pedestrians and motorized vehicles (e.g. Rosén and Sander, 2009).

Wrap projection and *forward projection* begin in similar ways. The first contact in these cases is often between the pedestrian´s leg or knee and the vehicle´s bumper (Stcherbatcheff et al., 1975, Ashton, 1978). The type and extent of injury sustained depends on the pedestrian´s height. A child might be struck above the knee, while an adult below the knee (Rooij et al., 2003), resulting in different kinds of injuries. This contact creates a rotating force that, combined with the fact that the pedestrian´s body is still travelling at slower speed than the vehicle is, causes the rest of the body to be struck by the front of the vehicle and be accelerated, though the pedestrian will still be travelling at lower speed compared to the vehicle´s impact speed (Ashton, 1978, Grandel et al., 1986). From this point on, wrap projection and forward projection differ. If the victim´s center of mass is above the height of the vehicle bonnet leading edge, the collision will most likely result in *wrap projection* (Wood et al., 2005). If the impact speed is sufficiently high the rotation force toward the bonnet might cause the pedestrian´s head, shoulders and chest to strike the bonnet, A pillar, or the window (Wood et al., 2005, Ashton et al., 1977) and continue to accelerate the victim to the vehicle´s impact speed. If the speed is high, the victim might simply fly over the vehicle (Ashton et al., 1977, Walz et al., 1986) [7]. If the vehicle has, at this point in the collision, started to brake then the victim will eventually have higher speed than the vehicle (the pedestrian accelerated to the vehicles speed, but the vehicle continues to slow down after the contact). This can result in that the victim is thrown forward to the ground where he or she will eventually come to a stop (Ashton et al., 1977, Ashton, 1978, Grandel et al., 1986, Wood et al., 2005).

If the victim´s center of gravity is lower than the leading edge of the vehicle´s bonnet, the collision will most likely be a forward projection. The pedestrian´s head and shoulders may be rotated and strike the bonnet, but the body will be thrust forward (Wood et al., 2005); that is, the victim will not slide up onto the bonnet, but will remain in front of the vehicle and be accelerated to the vehicle´s speed. When the vehicle brakes, the victim has higher speed than the vehicle and is therefore 'thrown' forward and hits the ground (Ashton, 1978, Wood et al., 2005). A special case of forward projection is a *run over accident*. There was little discussion in the literature regarding why some accidents become run over accidents. Simms and Wood (2009) discuss that this can occur when the car is braking (resulting in separation between

[7] The rotation force can result in the pedestrian being fully rotated. If this occurs on or over the bonnet, and the vehicle has at that moment lower speed than the pedestrian (so that the pedestrian will be moving forward compared to the vehicle) that is sometimes referred to as somersault. If the pedestrian is thrown over the roof, and lands behind the vehicle, that is sometimes refered to as roof vault (Simms and Wood, 2009).

the vehicle and pedestrian), but that if the vehicle is not braking sufficiently then the vehicle might go over the pedestrian, i.e. the vehicle will simply drive over the victim. Run over accidents are frequently excluded from injury studies (or are studied separately) because the injury mechanisms differ considerably. However, such accidents are very important since they often involve serious injuries (Ashton, 1979). Ashton (1979) showed that while 1.5% of pedestrian accidents involving children were run over accidents, they constituted almost half of the fatal pedestrian accidents for children. Even though Ashton´s study is relatively old and the composition of the vehicle fleet has changed since then, the findings demonstrates the importance of preventing those accidents.

The last accident type, *reverse accidents*, is rarely studied. In such accidents, the victim is often a child; these incidents frequently occur on driveways or parking lots (Brison et al., 1988). No study was identified analyzing the accident mechanisms for reverse accidents, but they are controlled by the same physical laws as the other accident types, therefore, they can be expected to be similar to forward projection or wrap projection, or like run over accidents in the case of young children. Even though it can be expected that the speed in those accidents is usually low, the injuries are often quite serious and therefore very important to consider. In a study conducted in the United States, examining accidents involving children four years old or younger, 24 of 71 of the fatal accidents were reverse accidents (Brison et al., 1988), a British study (Ashton, 1979) showed 2 of 15 fatal accidents to be reverse accidents (children 4 years and younger).

Since the underlying kinematics of an accident in essence constitute a physical relation, much of this should also apply to accidents between motorized vehicles and bicyclists. Both pedestrians and bicyclists are unprotected (compared to car occupants, who are located in a protective shell); both are much lighter than the motorized vehicle and both operate in initially similar conditions. But there are also some differences to consider. For one thing, bicyclists have higher centers of gravity than pedestrians do (Peng et al, 2012, Watson, 2010), and the interaction between bicyclists and motorized traffic differs from those between pedestrians and motorized vehicles, resulting in a different initial stance against the vehicle. Finally, bicyclists travel at higher speeds than pedestrians do. Simulation studies have shown that cyclists have a greater tendency to have a sliding phase over the bonnet compared to pedestrians (Maki et al., 2003, Watson, 2010), one simulation study showed the bicyclist to be rotated in the collision (Ito et al., 2014), and crash test with dummies have shown the head impact to be higher up on the car compared to struck pedestrians (van Schijndel et al., 2012).

Vehicle characteristic´s

Since the relative height of the victim and the front structure of the motorized vehicle influence the accident mechanisms, it is logical that the vehicle type, or to be more precise, the front structure of the vehicle, influences those mechanisms and the

resulting injuries. Roudsari et al. (2005) showed that the probability for struck pedestrians to be thrown forward or knocked down (similar definition to forward projection) was more than doubled for pedestrians struck by light truck vehicles (LTV) compared to passenger vehicles. Furthermore, the proportion of being thrown forward or knocked down was 93% for children struck by LTVs, compared to 46% for children struck by passenger vehicles (Roudsari et al., 2005). The high proportion is because of the lower height of the children.

Because vehicle type influences the accident mechanisms, it also influences the resulting injuries. Numerous studies have shown the vehicle type to be highly influential for the injury severity/outcome for struck pedestrians. Starnes and Longthorne (2003) showed that sport utility vehicles (SUVs), vans and pick-ups have a higher probability (per registered vehicle) of being involved in fatal pedestrian accidents, especially for children under age 15. In addition, studies that focus on the consequences, once an accident has occurred have shown larger vehicles, such as SUVs and trucks to involve an elevated risk of serious (Eluru et al., 2008, Lee and Abdel-Aty, 2005, Mizuno and Kajzer, 2000, Roudsari et al., 2004, Tay et al., 2011, Tefft, 2013) and fatal injuries (Ballesteros et al., 2004, Desapriya et al., 2010, Lefler and Gabler, 2004, Kim et al., 2008, Roudsari et al., 2004, Tay et al., 2011, Zahabi et al., 2011). Tefft (2013) however, did not show a statistically significant relation between LTVs and the probability of fatality. Some studies have shown this risk to vary between different body regions (i.e. the AIS body regions), where passenger vehicles caused more severe injuries to the lower extremities, while larger vehicles caused more severe injuries to the upper part of the body (Liu et al., 2002, Mizuno and Kajzer, 2000).

Since bicyclists have a higher stature in collisions (owing to their higher center of gravity), the influence of vehicle type on their injury severity/outcome can be expected to differ slightly from its influence on injury types for struck pedestrians. Earlier studies have shown an elevated risk of serious (Eluru et al., 2008, Kim et al., 2007, Moore et al., 2011, Wang et al., 2009, Yan et al., 2011) and fatal (Eluru et al., 2008, Kim et al., 2007, Maki et al., 2003) injuries for struck bicyclists.

There has been some discussion regarding what causes this elevation in the risk of injury. Desapriya et al. (2010) discussed that there are three design factors in which LTVs differ from passenger vehicles: they are heavier, stiffer and have higher bumpers. Ballesteros et al. (2004) also argued that even the weight of the vehicle is important. Mizuno and Kajzer (1999), however, reasoned that it is not the weight of the vehicle, but rather the front structure that is significant, because the weight difference between a pedestrian and a motorized vehicle (of any type) is already so great. That is, the correlation between weight and injury severity/outcome owes merely to the correlation between weight and vehicle type, hence, the importance of the vehicle´s front structure.

The impact speed

The impact speed can influence the accident mechanism, for example, at a low impact speed the victim might manage to avoid a head impact by putting up his or her hands for protection, something that would not be possible at higher speeds. The impact speed has, however, another very important role in the accident. It controls the forces and accelerations/decelerations that the victim is subjected to (these forces can be further divided into velocity change, peak deceleration, pulse duration, and more (Monea et al., 2014, Thomas et al., 2006)). Obviously, a higher speed will result in a blunter impact, which results in more serious injuries. Several studies have shown that the impact speed correlates highly with the risk of serious injuries (e.g. Rosén et al., 2009, Tefft, 2011, 2013) and with risk of fatal injuries (Davis, 2001, Kong and Yang, 2010, Richards, 2010, Rosén et al., 2009, Rosén and Sander, 2009, Tefft, 2011, 2013) for struck pedestrians. The absolute risk values have, however, been shown to vary between countries (Rosén et al., 2011), likely owing to under reporting (Elvik and Mysen, 1999) and population differences (e.g. age distribution and vehicle types).

While numerous studies were identified that examined the influence of impact speed on the probability of serious injuries and/or fatalities for struck pedestrians, only two studies were identified which investigated this relation for struck bicyclists. Rosén (2013) showed that higher impact speed was highly correlated with the risk of serious injuries and/or fatality. One additional study showed that the risk of a serious head injuries increased with higher impact speed (Nie and Yang, 2014); however, the dataset was small (*n = 24*). Since bicyclists can maintain high speeds in urban environments it is possible that the speed of the bicyclists themselves influences the injury severity/outcome. Rosén (2013) tested to include the bicyclist´s own impact speed in his study, however, this variable was not included in the final model because it did not improve that model. Maki et al. (2003) showed that, in 30 to 50 km/h speed zones in Japan, the impact speed of the cyclist was less than 10 km/h in 90% of the accidents, this can however be expected to vary between cities due to infrastructure design and traffic density.

Individual factors

The pedestrian´s initial stance is influential in the accident mechanisms. Simms and Wood (2006) showed that the head impact load is greatest if the pedestrian was facing the vehicle and lowest if the pedestrian was sideways towards the vehicle (i.e. perpendicular to the vehicle). Eluru et al. (2008) results align with this, where frontal impact were more likely to result in serious or fatal injuries compared to sideways impact. Other studies have demonstrated that the pedestrian stand was sideways towards the vehicle in the great majority of the accidents (Ashton, 1978, Chidester et al., 2001, Otte and Haasper, 2005, Otte and Huefner, 2007). The pedestrian´s height influences the height of the center of gravity, which in turn influences the accident mechanisms. Three studies included the victim´s height in the analysis and

showed that height was associated with injury severity (Isenberg et al., 1998, Tefft, 2013, Zhang et al., 2008) and the risk of fatality (Tefft, 2013). Even the weight (Tefft, 2013, Zhang et al., 2008) and body mass index (weight/height^2) has been shown to be correlated with the risk of severe injuries and/or fatality (Tefft, 2013). Kramlich et al. (2002) showed that children up till age of 10 years were less likely to impact the windscreen compared to adults.

Rosén (2013) showed that 65% of bicyclists who were struck by motorized vehicles were struck by the front of the vehicle: such accidents exhibit an overrepresentation of serious and fatal injuries. Otte and Haasper (2005) showed similar proportions (69%) where over half of those were facing sideways to the front of the vehicle. Other studies have shown 65-66% of the fatal accidents and 57.5-60% of the serious injury accidents to be sideways collisions (Huijbers, 1984, Maki and Kajzer, 2001), compared to 50.4% of the minor injury accidents (Maki and Kajzer, 2001). Eluru et al. (2008) showed that the risk of fatality was higher when the direction of impact with the cyclist was frontal compared to if the direction was sideways, however the results from Maki et al. (2003) might indicate that it matters if the bicyclists was riding in same or opposite direction compared to the motorized vehicle, which might perhaps explain the contradicting results. No study was found that investigated the influence of the bicyclist´s height on the injury severity and the probability of fatality. However, given that the center of gravity influences the accident mechanics and that height is associated with injury severity for struck pedestrians (Isenberg et al., 1998, Tefft, 2013), height might be important for bicyclists as well. One fundamental difference between pedestrians and bicyclists is that bicyclists sometimes wear a helmet, which has been shown to reduce the injury severity and injury outcome (e.g. Boufous et al., 2012, Kim et al., 2007, McNally and Rosenberg, 2013, Otte and Haasper, 2010), though, one study did not show helmet use to have any influence on injury severity or the probability of fatality (Rivara et al., 1997).

The physical condition of the victim is most frequently studied through the age of the victim. Several studies have shown senior pedestrians to have higher risk of fatality than younger pedestrians do (Ashton, 1978, Davis, 2001, Henary et al., 2006, Kim et al., 2010, Peng and Bongard, 1999, Tay et al., 2011). There are also many studies that show that even the risk of serious injuries increases with age (Ashton, 1978, Henary et al., 2006, Kong and Yang, 2010, Lee and Abdel-Aty, 2005, Tay et al., 2011, Zhang et al., 2008). The evidence therefore seems to be strong that age is a good proxy for the injury severity/outcome, and strongly related to it. But it is not only seniors who have elevated risk of fatal injuries. Some studies have shown higher risk even among younger groups. Kim et al. (2008) showed 55 to 64 years old to have elevated fatality risk and Gustafsson and Thulin (2003) did the same for the age group 45 to 64.

It is not only the oldest that show elevated fatality risk, Gustafsson and Thulin (2003) showed that children below age 7 also have an elevated fatality risk, and Zegeer et al. (1993) showed that children below age 11 had elevated risk of fatal injuries. Finally,

Pitt et al. (1990) showed that children aged 4 years old or younger have an elevated probability of sustaining serious injuries compared to older children.

Several studies have investigated the influence of age on injury severity and the probability of fatality for struck bicyclists. Seniors (usually defined as 65 years or older, although some studies use other age thresholds) have an elevated risk of serious injuries (Eluru et al., 2008, Yan et al., 2011, Sze et al., 2011). Seniors have also been shown to have elevated risk of fatal injuries (Eluru et al., 2008, Kim et al., 2007). There are even studies that show an elevated risk of serious (Kaplan et al., 2014, Rivara et al., 1997, Sze et al., 2011) and fatal (Kaplan et al., 2014) injuries for children. The studies that focused on children were not limited to collisions with motorized vehicles. Boufous et al. (2012) and Kramlich et al. (2002) could not identify any elevated risk of serious/severe and/or fatal injuries for children.

The literature, therefore seems to indicate that the probability of fatality, and perhaps even probability of serious injuries for struck pedestrians (and perhaps also for struck bicyclists), have a U shaped function, where the youngest and the oldest victim have the highest probability of fatality. It should be noted that not all studies show an elevated probability of fatality for children as pedestrians (Davis, 2001) or severe injuries for bicyclists (Boufous et al., 2012). It can be speculated that this elevated probability of serious injuries for seniors ows to preexisting health and physical conditions i.e. they are more fragile (Dehlin and Rundgren, 2007), and that the elevated fatality risk stems from that fact, in addition, older pedestrians might die from complications that younger pedestrians would have survived (Sklar et al., 1989). It is more difficult to speculate what might cause this seemingly increased risk for children. One possible explanation is that children are more prone to be involved in forward projection accidents (Roudsari et al., 2005) or overrun accidents, which tend to cause more serious injuries, because children are not as tall as adults.

Several other individual factors are also likely to influence the injury severity/outcome, e.g. sex, pre-existing medical conditions, biomechanical tolerance, muscle tone, stomach contents, alcohol consumption, and protective gear (Thomas et al., 2006). These factors however, lie outside the scope of this thesis and are not discussed further here.

Injury severity and injury outcome

The resulting injuries are a result of the combined effects of the accident mechanisms, the vehicle´s characteristics, the individual´s characteristics, physical conditions, and the impact speed (see model in figure 10). The accident mechanisms (which are influenced by the impact speed, vehicle characteristics and the individual characteristics) determine which parts of the victim´s body will sustain injuries, often ending with a *ground impact* (also often referred to as *secondary impact*). Since each injury or body region has its own prognosis, it is important where on the body the sustained injuries are and what part of the vehicle, or ground, caused that injury.

The most frequent minor injuries for struck pedestrians are injuries to the lower extremities, usually followed by head injuries (Ashton et al., 1977, Otte and Haasper, 2005, Zhang et al., 2008). This should come as no surprise, given that most collisions (accident mechanisms) begin with an impact between the front of the vehicle and the lower extremities. One study, however, showed head and neck injuries to be the most frequent injuries (Peng and Bongard, 1999). Isenberg et al. (1998) combined all injury severities and showed that the most frequent injuries to be lower extremities, followed by injuries to the upper extremities, and then head injuries. Mizuno (2005) combined datasets from five countries that showed that of the AIS 2-6 injuries, the head was the most frequent body area to sustain injuries, followed by the legs, except in the data from Australia, where this order was reversed.

When focusing on the more serious injuries or fatalities, the literature goes in two directions: (a) As the injuries get more serious, the head injuries become the most frequent injuries (Ashton, 1978, Andersson and McLean, 2001, Falkenberg, 2008, Kramlich et al., 2002, Zhang et al., 2008), often followed by injuries to the lower extremities, torso, thorax and/or chest injuries (Andersson and McLean, 2001, Ashton, 1980, Falkenberg, 2008, Kramlich et al., 2002, Zhang et al., 2008); or (b) on injuries to the lower extremities and/or pelvis followed by head injuries (Fredriksson et al., 2010, Maki et al., 2003, Strandroth et al., 2011). It is of great interest, even though injuries of all AIS values can result in fatalities, to consider which injuries are the most life threatening. Several studies have shown that a great majority of AIS5+ injuries are head injuries (Ashton, 1978, Zhao et al., 2010). Other studies have shown that most of the fatal injuries are head injuries (Ashton, 1979, Ashton, 1980, Brison et al., 1988, Falkenberg, 2008, Maki et al., 2003, Oh et al., 2008, Tharp and Tsongons, 1977, Zhao et al., 2010) or head/neck injuries (Harruff et al., 1998).

Let us now take a look at bicyclists. Otte and Haasper (2005) based their analysis on two large dataset (2 304 and 2 018, from 1985-1993 and 1995-2003) and showed that the most frequent injuries for struck bicyclists (all injury severities) were lower extremities, followed by upper extremities and head injuries (the frequency of upper extremities and head injuries was similar, however, for the newer dataset upper extremities were second most frequent, while the head injuries were second most frequent for the older dataset). Juhra et al. (2012) showed upper extremity injuries to be most frequent, then lower extremity injuries, followed by head injuries, but that study was not limited to collisions between motorized vehicles and bicyclists. Haileyesus et al (2007) showed that the most frequently injured region of the body was the head/neck area, followed by the lower extremities, then the trunk. The most frequent serious injuries for struck bicyclists vary somewhat between studies. Maki et al. (2003) showed lower extremity injuries, followed by head injuries, then upper extremity and chest injuries to be the most frequent serious injuries that occurred in 30-50 km/h speed environment in Japan. Falkenberg (2008) showed the most frequent serious injuries for struck bicyclists to be head injuries. Maki et al. (2003) showed that the head injuries comprised 72% of the fatal injuries, followed by chest

and neck injuries and Falkenberg (2008) shows the most frequent fatal injuries to be head injuries, followed by thorax injuries.

Given the frequency of head injuries among the most serious injuries, for both pedestrians and bicyclists, it is of interest that serious head injuries (AIS3+) are found in all age groups of struck pedestrians already in the impact speed interval 21-30 km/h (Andersson and McLean, 2001, Ashton, 1978) and the proportion of victims who sustain head injuries, along with the severity of those head injuries, increases with higher impact speed (Ashton, 1978, Walz et al., 1986). Ashton (1978) showed that the head struck the vehicle in two thirds of accidents involving passenger vehicles and that the proportion increased with higher impact speed.

Roudsari et al. (2005) showed that most of the head injuries from collisions between pedestrians and passenger vehicle, resulted from impacts with the lower edge of the window, the bonnet and the A pillar. This differed for children, owing to their lower statue. Children´s heads most frequently made contact with the bonnet, window or the ground. Other studies have shown the most frequent source of serious head injuries to be result from impact with the windscreen, ground and bonnet (Fredriksson et al., 2010), but there has also been mentions of the A pillar (Mizuno and Kajzer, 2000).

Even though the impact with the vehicle is usually responsible for the most serious injuries experienced by struck pedestrians (Ashton, 1978, Walz et al., 1986) the final impact when the victim strikes the ground, can result in severe injuries too (Walz et al., 1986). Ashton et al. (1977) found AIS6 injuries from ground impact for struck pedestrians, and other studies have estimated that the impact with the ground was responsible for between 19% and 48% of the minor head injuries sustained by struck pedestrians (the criteria differ slightly between studies; Badea-Romero and Lenard, 2013, Cuerden et al., 2007, Falkenberg, 2008, Mizuno and Kajzer, 2000); the proportion of injuries caused by ground impact is lower for the more serious head injuries (AIS3+; Badae-Romero and Lenard, 2013, Mizuno and Kajzer, 2000). In addition, the vehicle type, which affects the accident mechanisms, seems to influence the severity of head injuries that result from impact with the ground. Roudsari et al. (2005) showed that LTV accidents result in higher AIS values owing to ground impact. It is possible that the source of injuries might differ between struck bicyclists and struck pedestrians, because of the cyclist´s higher initial stance and higher speed of the bicyclist himself (Peng et al., 2012), but Baedea-Romero and Lenard (2013) showed that among struck bicyclists, the ground was the source of 69% of the head injuries, and the vehicle was the source of 31% of the head injuries.

Post collision

Most struck pedestrians who eventually die after an accident, survive long enough to start receiving medical care (Atkins et al., 1988, Harruff et al., 1998, Mueller et al., 1988, Schmucker et al., 2010, Walz et al., 1983). Sánchez-Mangas et al. (2010) showed, for all accident types combined, that the fatality risk was related to the

medical response time. Mueller et al. (1988) and Ashton (1978) showed that the probability of fatality is greater in rural areas than it is in urban areas, and Kaplan and Prato (2013) show, by applying model based clustering that accident groups occurring in rural settings had higher injury severity/outcome compared to accidents in urban settings. Mueller et al. (1988) discussed the possibility that this might have to do with the availability and quality of health care, whereas some injuries are fatal only if the victim does not receive medical aid in time (Somers, 1983). There might also be other explanations, such as higher speeds in rural settings or higher underreporting of non-fatal accidents. It is, however, important that the prognosis of the victim might relate to what occurs after the collision.

1.4 Knowledge gaps and research topics

Through the years, extensive research has been conducted concerning accidents between pedestrians and motorized vehicles and those between bicyclists and motorized vehicles. Despite this, the literature review reveals several knowledge gaps and interesting research topics that require further attention, some of which fall within the scope of this thesis:

(1) The relation between the number of accidents involving vulnerable road users and exposure has been explored before (e.g. Brüde and Larsson, 1993, Elvik, 2009a, Jonsson, 2005), and those studies have found a nonlinear relation, i.e. a safety in numbers effect. This effect can, however, be expected to vary between countries owing to specific situations and to traffic culture in each country, and it varies for intersections and for links. Jonsson (2005) created a safety performance function to study this phenomenon for links in Sweden, and Brüde and Larsson (1993) created a safety performance function for intersections in Sweden. The model from Brüde and Larsson (1993) was based on police reported accidents. Now we have access to hospital reports from STRADA, which has considerable influence on the reporting degree of accidents (Jonsson et al., 2011). Therefore, it is of interest to explore this relation, for pedestrians and bicyclists struck by motorized vehicles for intersections in Sweden.

(2) To create a safety performance function for this relation requires extensive field measurement to determine the exposure of pedestrians and bicyclists. This has resulted in that some of previous models (e.g. Jonsson, 2005, 2013, Schepers et al., 2011) have been based on short observational periods per site. There is, however, limited knowledge available about how this influences the validity (how well the model describes the reality) and reliability (how much the models, meant to describe the reality, might vary if performed several times) of those models. This methodological issue needs to be explored.

(3) Recently, it has come to our attention that the most frequently used results (Anderson et al., 1997, Pasanen, 1992, Teichgräber, 1983) about the importance of impact speed and the risk of fatality are not representable for the current situation (Davis, 2001, Richards, 2010, Rosén et al., 2011, Rosén and Sander, 2009), two of those are based on biased data (Anderson et al., 1997, Pasanen, 1992) and the third was focused on area with abnormal age composition, and is over 50 years old (Teichgräber, 1983). New results show that the risk of fatality is much lower than previously believed (Richards, 2010, Rosén and Sander, 2009, Tefft, 2011). It is necessary to investigate what happened and to determine which results are the most reliable, why the interpretation is faulty and how it can be improved so that we may better understand those fatality risk curves and adjust speed policies and traffic planning accordingly.

(4) The relation between impact speed and the risk of fatality for struck pedestrians is very direct; it is, in essence, a physical relation (though individual characteristics will also influence this relation). However, the speed policy is not based on impact speed. It is therefore of interest to see how the injury severity/outcome relates to the speed environment at accident sites. To my knowledge, no one has attempted to analyze the relation between mean travel speed and the injury severity/outcome for pedestrians and bicyclists struck by motorized vehicles.

(5) Age has been found to be highly influential for the injury severity/outcome for struck pedestrians (e.g. Henary et al., 2006) and bicyclists (e.g. Eluru et al., 2008). It is therefore also of interest to include age of the victim in the analysis, in order both to control for it, and to gain an even better understanding of how age affects the injury severity/outcome for those two groups.

(6) Hundreds of studies focus on accidents between pedestrians and motorized vehicles and/or bicyclists and motorized vehicles. Pedestrians and bicyclists have a great deal in common when it comes to accidents; however, there are distinguishing differences (Maki et al., 2003, Watson, 2010). Since those road user groups are among the most fragile found in the traffic environment, and because they are often treated as a single group, they are often supposed to use the same facilities when it comes to interacting with motorized traffic. For this reason, it is interesting to ask what their similarities and differences are in terms of injury severity/outcomes when one or the other is struck by a motorized vehicle.

2. Aim and scope

The aim of this work is to study accidents between pedestrians and motorized vehicles and those between bicyclists and motorized vehicles. This work is divided into two studies: Study I examines the relations between the risk (i.e. the risk of an accident occurring) and exposure, and Study II explores the probability of a certain injury severity/outcome for the victim (i.e. the struck pedestrian or bicyclist). The work seeks to investigate six research questions:

Study I

1. What is the relation between the volumes of pedestrians and bicyclists and the number of accidents for those road user groups?
2. How does the reliability and validity of safety performance functions vary owing to the length of observational periods concerning exposure?

Study II

3. How to interpret the relation between impact speed and injury level of pedestrians struck by motorized vehicles, and what are the implications for speed policy?
4. What is the relation between the speed environment at the accident site and the injury severity/outcome for pedestrians and bicyclists struck by motorized vehicles?
5. What is the relation between the age of the victim and the injury severity/outcome of pedestrians and bicyclists struck by motorized vehicles?
6. What are the differences in injury severity/outcome for pedestrians and bicyclists, struck by motorized vehicles?

This work uses the approach suggested by Nilsson (2004) of dividing the problem into three dimensions: *exposure, risk* and *consequence.* The thesis is composed of four journal articles. The papers' relations to those dimensions are shown in figure 11.

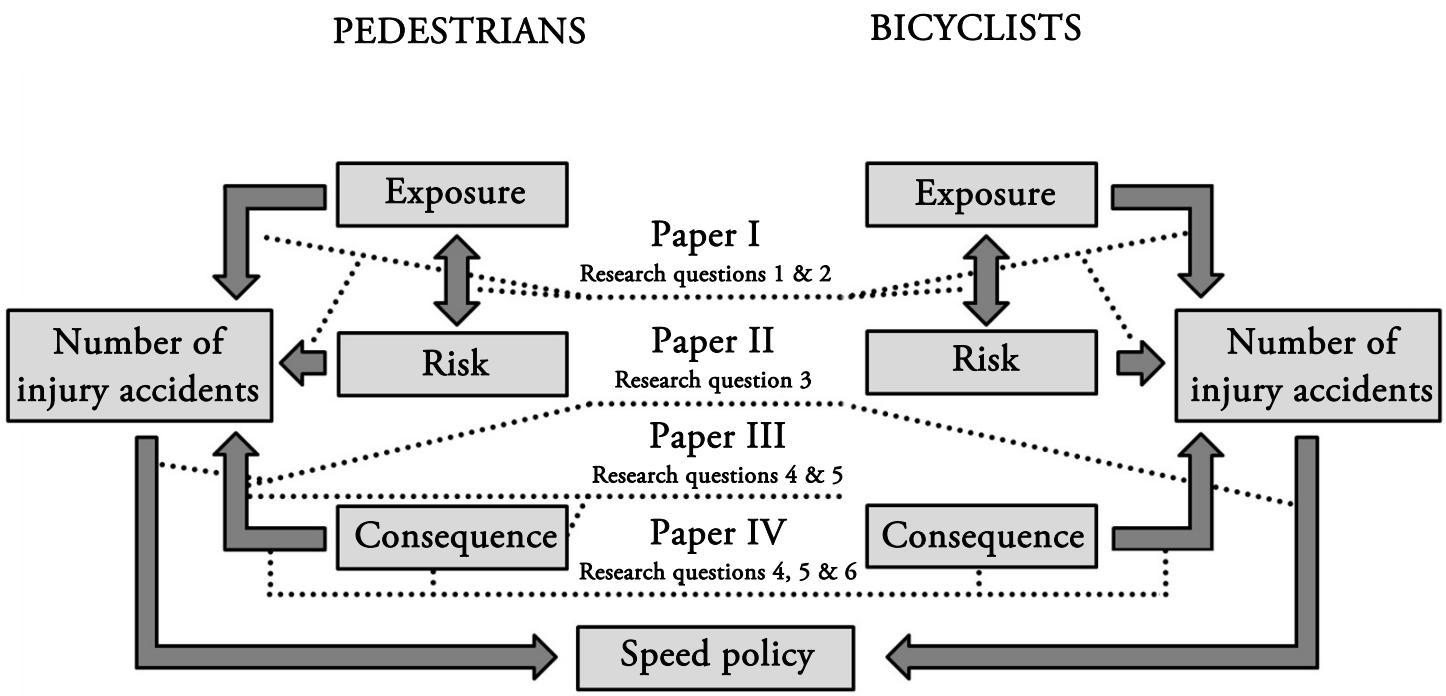

Figure 11: Overview of how the papers relate to the accident problem involving pedestrians and bicyclists and which research questions each aims to address.

3. Methods

3.1 Study 1

The method for study 1 is described in detail in *paper I*. To fulfill the aims of this part of the project, several accident models (safety performance functions) were created for four accident types:

Model i	Single pedestrian accidents.
Model ii	Single bicyclist accidents.
Model iii	Accidents between pedestrian and motorized vehicle.
Model iv	Accidents between bicyclist and motorized vehicle.

The working process is divided into five steps:

(1) Selection of sites for data collection (observation sites).

(2) Compilation of accident data at the sites.

(3) Data collection, which includes geometric data (description of the traffic environment) and exposure data (traffic volumes for pedestrians, bicyclists and motorized vehicles).

(4) Processing the exposure data.

(5) Statistical modelling and sensitivity analysis (i.e. creation of safety performance functions).

3.1.1 Site selection

The study focused on mid-size Swedish cities. For a city to be eligible for the study it had to fulfill three criteria: (a) the population of the municipality had to be between 50 and 200 thousands, (b) traffic accidents were registered in STRADA for the years 2008 to 2012 and (c) the city must have at least 10 main street intersections within city limits that were eligible for the study. Six cities were selected:

Eskilstuna	(99 729 inhabitants)	
Halmstad	(94 084 inhabitants)	
Helsingborg	(132 989 inhabitants)	
Kalmar	(63 887 inhabitants)	
Kristianstad	(81 009 inhabitants)	
Västerås	(142 131 inhabitants)	(SCB, 2014)

I decided to focus on intersections. The reason for this is that a recent study focused on this relation at links in Sweden (Jonsson, 2005); while a published scientific study of this type for intersections in Sweden (Brüde and Larsson, 1993), are much older and were performed before STRADA was created, hence, do not include accidents registered only by hospital. Inclusion criteria for a site comprised the following: it should not be a roundabout (traffic flows and interactions in roundabouts might differ from those in other intersection types, suggesting they are best analyzed separately), there must be some potential for pedestrian and bicyclist flows on the site, and nothing to suggest recent changes in the traffic environment had taken place, which might have considerable influence on the accident risk, hence influence the models. Ultimately, 113 sites were included in the dataset, but the number of sites was limited so that it would be possible to perform longer observations at each site.

3.1.2 Compilation of accident data

All the accidents that had occurred at a site between 2008 and 2012 and that were registered in STRADA were compiled and divided into four accident types:

(i) Single pedestrian accidents.

(ii) Single bicyclist accidents.

(iii) Accidents between pedestrian and motorized vehicle.

(iv) Accidents between bicyclist and motorized vehicle.

If it was unclear whether the accident related to the intersection or to the nearby links, the accident description was reviewed in order to categorize the accident correctly.

3.1.3 Data collection

Geometrical data were collected at each site to describe the physical layout of the traffic environment. This included factors such as city, traffic environment, the intersection´s control mechanism, speed limit, whether it was a three- or four-leg

intersection, bicyclist integration with motorized traffic, the number of intersection legs crossable by pedestrians/bicyclists, and whether there was a traffic refuge, speed hump or crosswalk.

The exposure data comprised four variables: (1) flow of motorized vehicles entering the intersection, (2) the number of times a pedestrian crossed a street, (3) the number of pedestrians who entered the intersection but did not cross a street, and (4) the number of bicyclists who entered the intersection. The flow of motorized vehicles was acquired from the municipalities. In some cases no measurement was available, and the flow had to be estimated from the number of houses, traffic volume on nearby streets, and other factors. Most measurements were taken within the preceding five years, and the traffic volumes were scaled to be representative for the year 2012 (The Swedish Road Administration, 2013). The pedestrian and bicyclist flows were counted for 3 one hour periods at each site. The measurements were performed in spring/fall and to reduce the influence of the weather, no measurements were taken if it was raining or if the temperature was low since that might influence the number of pedestrians and bicyclists. The observational periods were as follows:

Morning	Afternoon
8:30-9:30	13:30-14:30
9:45-10:45	14:45-15:45
11:00-12:00	16:00-17:00

The observational periods were purposely chosen to try to avoid peak hours for pedestrians and bicyclists, because the peak hour for pedestrians and bicyclists can be very brief and extreme (Jonsson, 2005). If observations had been made during peak hours at a given site, and the peak time differed from the time that the scaling´s peak hour was based on, this might cause problems with the scaling of the exposure data.

The logic of counting the number of times a single pedestrian crossed a street is based on the assumption that crossing a street involves some risk; therefore, crossing two streets should involve greater risk than crossing only one street. Counting the number of pedestrians alone would not take this into consideration. The pedestrians who entered the intersection without crossing a street were counted for the modelling of single pedestrian accidents. Initially, the thought was to divide the number of cyclists according to their interaction with the motorized traffic; however, due to that the interaction between bicyclists and the motorized traffic varied extensively, it would have been impractical to divide them into groups.

3.1.4 Processing the exposure data

Several datasets, based on observational periods of different lengths, were created. The first dataset was based on 180 minutes of observations at each site for respective road user groups (pedestrians, bicyclists, etc.). Since one aim of this study was to investigate the influence of the length of observational periods on the validity and reliability of safety performance functions, it was necessary to create different datasets for observational periods of varying lengths, i.e. to simulate that the data collection was based on shorter observational periods than it actually was. For this purpose, 10 datasets were created for each observational period (i.e. 10 datasets based on 15 minutes of observations, 10 datasets based on 30 minutes of observations, etc.), where the time period at each individual site was chosen at random from the full 180 minutes of observations. This way, there were 10 datasets for each specific observational period length, where each might represent one hypothetical study. This method simulates if there had been 10 independent data collections based on 15 (30, 45, etc.) minutes of observations at each site.

The traffic volumes vary by times of day (Jonsson, 2005); hence, using unscaled exposure data for one time period at site A and for another time period at site B might introduce bias into the analysis. Therefore the exposure data were scaled to render them comparable across sites. This was a three step process:

(1) External data (Ahlström, 2013, Indebetou and Quester, 2007, Jonsson, 2005) were used to determine what proportion of the daily traffic volume occurs during the observational period (i.e. 8:30-12:00 and/or 13:30-17:00).

(2) The observations were divided into four groups (a: central and residential areas and b: arterials, industrial and rural areas | A: morning observation and B: afternoon observation)

(3) From this, twelve exposure distribution curves were estimated (two time periods | two traffic environment types | three road user groups). This way, a scale factor was estimated for each 15 minute interval and used to scale the exposure measures for each interval, making it comparable (as an average daily value).

Although this approach has some limitations, it provides the best data available and should provide an acceptable basis for the scaling process.

3.1.5 Descriptive statistics

Figures 12 to 15 show descriptive statistics for the intersections in the study. In some cases, several groups were combined in the modelling process because there were too few sites for that particular group, e.g. rural and industrial areas; right of way, yield and stop signs; some speed environments etc. Figures 16 and 17 show the cumulative

distribution of exposure for the various intersections in the study. Figure 18 shows descriptive statistics for the number of accidents of different types in the intersections, demonstrating that the great majority of the intersections had zero accidents during the study period. Such a great proportion of zero accidents is common in accident modelling. Finally, table 1 shows descriptive statistics for the exposure depending on observational period length.

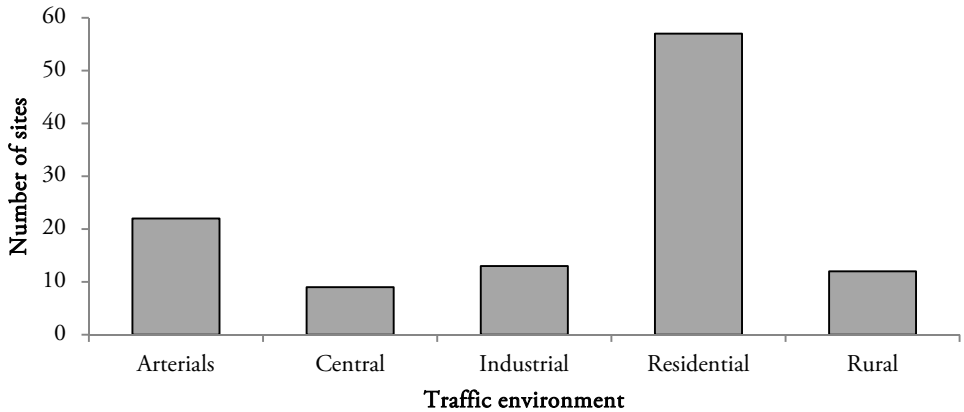

Figure 12: Number of sites by traffic environment.

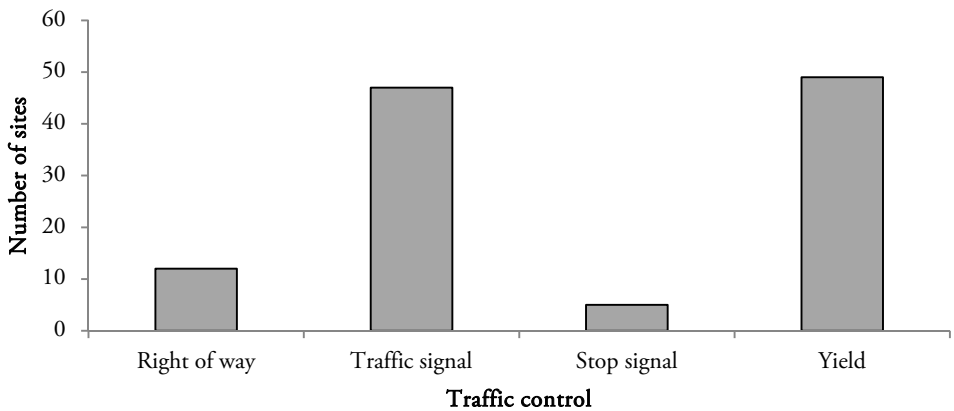

Figure 13: Number of sites by traffic control.

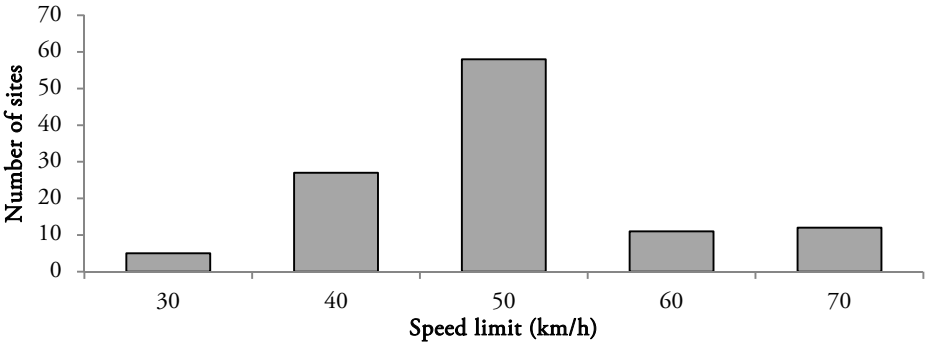

Figure 14: Number of sites by speed limit.

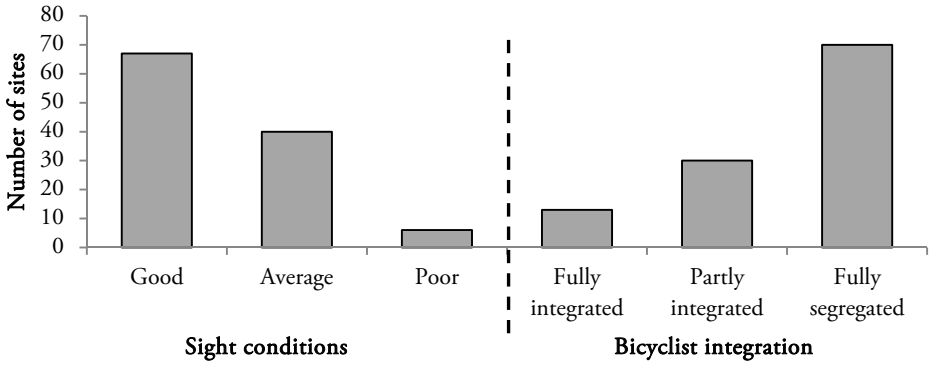

Figure 15: Number of sites by sight conditions and bicyclist integration with motorized traffic.

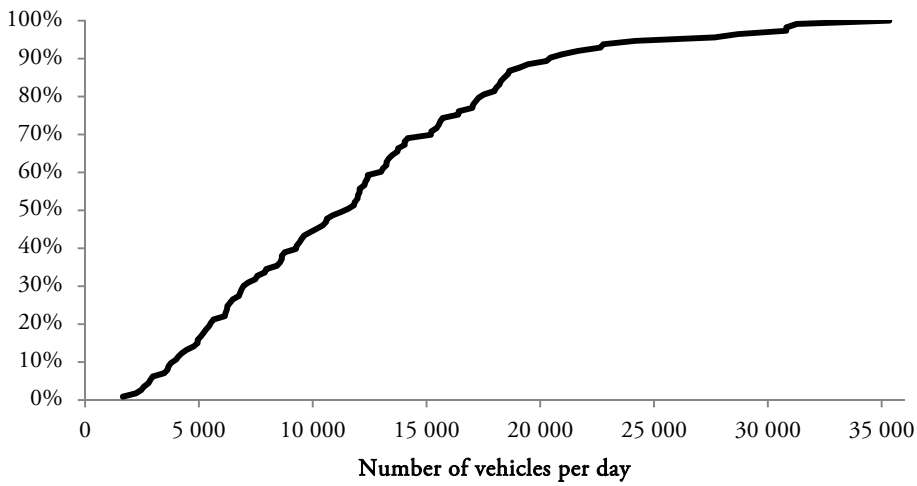

Figure 16: Cumulative distribution of sites by traffic flows of motorized vehicles.

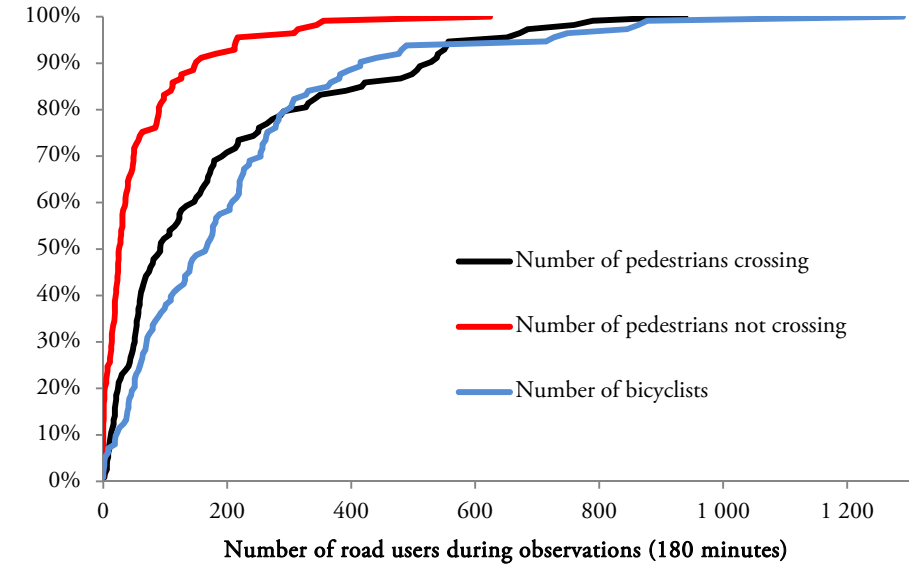

Figure 17: Cumulative distribution of sites by traffic flows of pedestrians and bicyclists

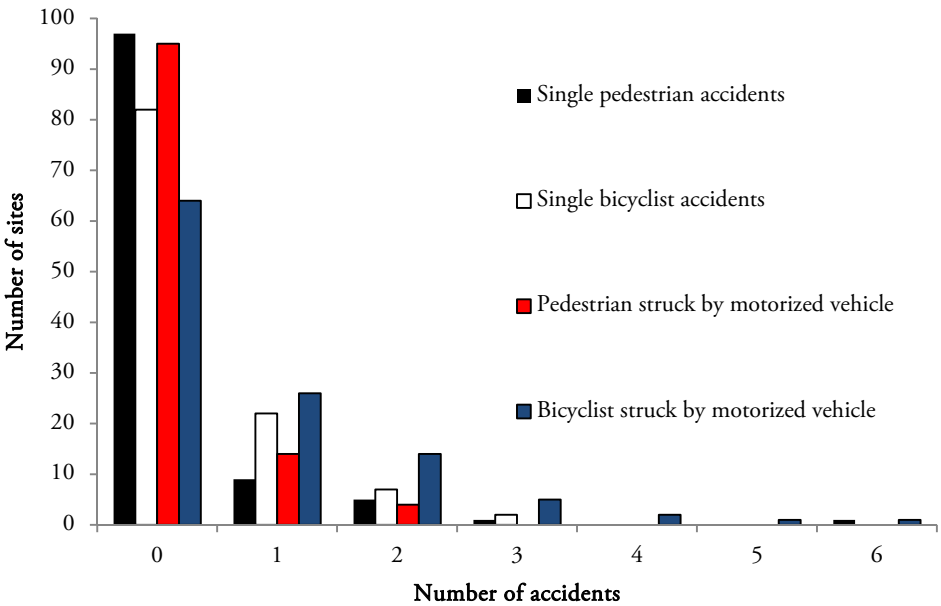

Figure 18: Number of accidents at intersections by accident types.

Table 1: Descriptive statistics for exposure at different sites (average daily exposure) and different time periods, depending on length of observational periods (all datasets, i.e. each site is included 10 times. If no road user was observed during the time period, the exposure was automatically set to 1).

	Length of observational period (minutes)						
	15	30	45	60	90	120	180
Number of pedestrian crossings							
Mean value	714	708	710	732	724	727	718
Minimum value	1	1	1	1	1	1	10
Maximum value	7 790	5 886	5 499	5 004	4 628	4 642	4 115
Number of pedestrians not crossing							
Mean value	235	234	229	232	231	231	226
Minimum value	1	1	1	1	1	1	1
Maximum value	2 782	2 359	2 430	2 206	1 989	1 900	1 955
Number of bicyclists							
Mean value	1 227	1 181	1 187	1 193	1 187	1 182	1 188
Minimum value	1	1	1	1	1	1	1
Maximum value	24 213	20 585	19 603	20 445	17 796	16 921	15 087

3.1.6 Statistical modelling and sensitivity analysis

Several available statistical models can be used to estimate a safety performance function, each with its own set of strengths and weaknesses. Poisson models were initially popular (Geyer et al., 2006, Ye et al., 2013); however, those models cannot handle the over dispersion, which is frequently observed in accident data (e.g. Cameron and Trivedi, 1990); negative binomial regression is better suited to handle this phenomenon (e.g. Poch and Mannering, 1996). Some researchers have suggested using zero inflated models because accident data often includes unusually high proportion of zero counts (e.g. Chin and Quddus, 2003), however, even though this gives a better fit of the data (Lord et al., 2005), the assumption of those models that some sites are safe (that there is zero probability of an accident occurring) may be inaccurate assumption, since no traffic site is safe (Lord et al., 2007). Therefore, the negative binomial regression was chosen as the most suitable option for this study.

The 180 minute datasets were used to create a base model for each accident type, both in order to analyze the relation between the number of accidents and the exposure; and in order to estimate the reliability and validity of models based on shorter observational periods. If there was a correlation between the different accident types, the models might have been improved by applying multivariate analysis (Mannering and Bhat, 2014); however, when controlled for exposure, those accidents showed low correlation, suggesting that traditional analysis (negative binomial regression) would suffice.

The modelling process started with the primary exposure variable (model i: number of pedestrians not crossing a street; model ii and iv: number of bicyclists; and model iii: number of pedestrians crossing a street). For models iii and iv, the exposure for motorized vehicles was added. For model i (single pedestrian accident) it would have been preferable to use all pedestrians who entered the intersection (not only those who entered without crossing a street), but since the data did not include the number of pedestrians who crossed a street (only how often a street was crossed), this was not possible. It is problematic to include the exposure variable for motorized vehicles in the models because it correlates with the primary exposure variable ($Corr_{LN(Ped.\ crossing)\ -\ LN(Mot.\ veh.)}=0.41$, $Corr_{LN(Bicyclists)\ -\ LN(Mot.\ veh.)}=0.55$). Nevertheless, since both variables are important to the probability of an interaction between those two road user groups, and thus also to the probability of a collision occurring; and because this is 'common practice' when estimating safety performance functions (Elvik, 2009a), the inclusion was deemed acceptable.

Next, it was tested to include the geometrical variables into the models (pedestrian crossing was excluded owing to a high correlation to traffic volumes); however, only one of those variables was statistically significant ($p<0.05$) in one model, and the logical link between this variable and the accident type was limited (model iii, pedestrians-motorized vehicle collisions; the variable was bicycle integration with motorized traffic). Excluding all the geometric variables might result in biased estimates of the models (Mannering and Bhat, 2014). Therefore the modelling continued with two parallel approaches: (a) models based only on the exposure variables (here from referred to as parsimonious models) and (b) models that included geometric variables based on a sensitivity analysis (here from referred to as fully specified model).

The sensitivity analysis was performed in the following manner: each geometric variable was added to the parsimonious model while investigating how great an influence each one had on the parameters of the exposure variables. If the influence was greater than 5%, that variable was included in the fully specified model (i.e. the fully specified model included all variables with influence greater than 5%). Finally, the models for the shorter observational periods were created based on the variables included in the base models.

To test the reliability and validity[8] of the models based on shorter observational periods, it was assumed that the base model was an accurate estimation. This is, of course, not entirely accurate because those models can be expected to deviate from those based on longer observational periods given that exposure may vary across days, weeks, and years (Ahlström, 2013, Esaway et al., 2013). Even so, this approach allows one to grasp the influence that the of length of the observational periods had on the accident models. Safety performance functions were estimated for all the datasets based on shorter observational periods (including the same variables as the base models so that they would be comparable). Five estimates were used to compare those models to the base models:

(1) The parameters of the safety performance functions, i.e. β_i.

(2) Akaike information criterion (AIC value).

(3) The significance level of the model´s parameters (the p values).

(4) The Standard error values of the parameters of the models.

(5) The mean absolute residuals of the models (see equation 5).

$$\textit{Equation 5:} \qquad \textit{Mean absolute residuals} = \frac{\sum|Residuals|}{Number\ of\ sites}$$

Some would suggest that the most appropriate way to compare econometric models such of those is by using elasticity factors, which are a measurement of how great of an influence a 1% change in the independent variable will have on the dependent variable (Washington et al., 2013). However, the elasticity factor is a direct product of the parameters of the model, hence, both approaches will show similar effect.

This thesis focuses only on accidents between motorized vehicles and pedestrians or bicyclists. Nevertheless, the models for the single pedestrian and single bicyclist accidents were used to gain a better understanding of the factors that might be behind the observed relations between exposure and risk.

[8] The models based on shorter observational periods are compared to a model based on three hours of observations. Therefore, validity is tested indirectly, by comparing the models based on shorter observational periods to the base models instead of comparing the former to the real average daily traffic volumes. Testing the real validity of a model describing this relation would require comparing the model to the real relation between exposure and the number of accidents. That relation, however, most likely relates to the exposure at the time of the accidents, not to the average daily traffic volumes, which are challenging and currently impractical to investigate. Further, Mensah and Hauer (1998) have demonstrated that long observational periods can be counterproductive.

3.2 Study 2

The methods applied in study 2 are described in detail in *papers II, III* and *IV*. *Paper II* forms the theoretical basis for the work investingating the importance of speed and other factors for the consequences that arise once an accident has occurred. It focuses on accidents between motorized vehicles and pedestrians and takes as its starting point an extensive literature review of current relations between impact speed and the risk of fatality among pedestrians struck by motorized vehicles. From there, it seeks a better and deeper understanding of how those results, especially as injury risk values or injury risk curves, influence the number of fatal accidents, of how reliable those results are and of the implications of those results for continued work to reduce the number of fatal accidents.

In order to gain a better understanding of the implications of the fatality risk curves for the number of fatal accidents, a relative approach (i.e. how does the probability of fatality change) was applied to the absolute fatality risk curves (what is the probability of fatality, given involvement in an accident at a given speed). This resulted in a new model, the relative fatality risk curve, which is based on the absolute fatality risk curves. The mathematical model for the relative fatality risk curve is described by equation 6, where RR_i is the relative risk of fatality (or the injury described by the absolute risk curve the model is based on), v is the impact speed, and dv is the deviation from that speed (hence, the relative risk ratio is for the difference from speed v to speed $v+dv$) and $P_i(v)$ is the absolute fatality risk for the impact speed v or $v+dv$. The relative risk ratio then describes how the theoretical number of fatal accidents might change proportionally if the speed changes from v to $v+dv$, see equation 6.

$$\textit{Equation 6:} \qquad RR_i(v, dv) = P_i(v + dv)/P_i(v)$$

To test this model, two different absolute fatality risk curves were applied (Rosén and Sander, 2009, Tefft, 2011) and the results analyzed. To test the reliability of the model a mathematical computation was applied, where the sensitivity of the relative risk ratio was tested for changes in the absolute fatality risk curve; see detailed description in *paper II*.

The latter part of study 2, *papers III* and *IV*, examines how the mean travel speed at accident locations and the age of the victim relate to the consequences for pedestrians and bicyclists who are involved in a collision with a motorized vehicle.

The analyses presented in the papers apply two separate datasets each (two for pedestrians and two for bicyclists). Dataset 1, includes all injury accidents between motorized vehicles and a pedestrian or bicyclist, that occurred in Sweden between 2004 and 2008 in which the victim´s age was known. This was to investigate and control for the influence of age. The second dataset was a sub sample of the other

datasets: accident locations were selected randomly (stratified with injury severity) from those that fulfilled ten additional criteria:

(1) The accident occurred in Scania.

(2) If the accident was not fatal, there was a hospital report to facilitate accurate determination of injury severity.

(3) Road conditions were not snowy nor foggy at the time of the accident.

(4) The accident occurred sometimes between 7:00 and 19:00.

(5) The injury severity was deemed related to the speed of the motorized vehicle.

(6) It was determined that there was no special situation at the time of the accident that could be expected to have considerable effect on the travel speed of the vehicle involved.

(7) The location of the accident and the direction of the vehicle were known.

(8) No considerable changes in the traffic environment that could have influenced the speed level were implemented after the accident occurred

(9) The location did not have a very low traffic volumes.

(10) The quality of the accident report was not deemed questionable.

From those, 156 accident sites (79 where a pedestrian was struck by a motorized vehicle and 77 where a bicyclist was struck by a motorized vehicle) were chosen for site measurements of speed. The mean travel speed (mean spot speed) of the traffic flow involved in the accident was measured in the precise location of the accident. See descriptive statistics for the datasets in table 2.

The relation of the mean travel speed, the victim´s age and the vehicle type to the injury severity/outcome was analyzed using standard statistical methods and a multinomial logit model. The resulting probabilities, according to the model, for different injury severities/outcomes can be calculated from equation 7, where P_i is the probability of injury severity/outcome i, x_{ik} are the dependent variables in the model (mean travel speed, age and vehicle type) for injury severity/outcome i, and β_i are constants. The relations were scaled for the outcome based sampling strategy. See detailed description of the methodology for a multinomial logit model and the scaling of the data (owing to stratification) in *papers III* and *IV*.

Equation 7: $$P_i = \frac{e^{\beta_{i0}+\sum \beta_{ik} X_{ik}}}{\sum e^{\beta_{jo}+\sum \beta_{jk} X_{jk}}}$$

Table 2: Descriptive statistics for the datasets in study.

	Pedestrians		Bicyclists	
	Dataset 1	**Dataset 2**	**Dataset 1**	**Dataset 2**
Minor injuries	6 474 (79.3%)	31 (39.2%)	8 231 (87.6%)	32 (41.6%)
Serious injuries	1 420 (17.4%)	29 (36.7%)	1 058 (11.3%)	30 (39.0%)
Fatal injuries	272 (3.3%)	19 (24.1%)	107 (1.1%)	15 (19.5%)
Total	8 166 (100%)	79 (100%)	9 396 (100%)	77 (100%)
Vehicle type				
Passenger vehicle/unknown	7 860 (96.3%)	71 (89.9%)	9 136 (97.2%)	71 (92.2%)
Heavy vehicle	306 (3.7%)	8 (10.1%)	260 (2.8%)	6 (7.8%)
Speed limit				
Unknown	4 566 (55.9%)	11 (13.9%)	5 188 (55.2%)	25 (32.5%)
20-30 km/h	405 (5.0%)	1 (1.3%)	353 (3.8%)	2 (2.6%)
40-50 km/h	2 771 (33.9%)	63 (79.7%)	3 558 (37.9%)	41 (53.2%)
60-70 km/h	255 (3.1%)	2 (2.5%)	216 (2.3%)	7 (9.1%)
80+ km/h	169 (2.1%)	2 (2.5%)	81 (0.9%)	2 (2.6%)
Age group				
0-6	240 (2.9%)	3 (3.8%)	93 (1.0%)	0 (0%)
7-15	1 090 (13.3%)	10 (12.7%)	1 688 (18.0%)	9 (11.7%)
16-24	1 728 (21.2%)	7 (8.9%)	1 775 (18.9%)	8 (10.4%)
25-34	984 (12.0%)	6 (7.6%)	1 343 (14.3%)	7 (9.1%)
35-44	892 (10.9%)	5 (6.3%)	1 280 (13.6%)	11 (14.3%)
45-54	813 (10.0%)	6 (7.6%)	1 169 (12.4%)	8 (10.4%)
55-64	823 (10.1%)	8 (10.1%)	1 024 (10.9%)	12 (15.6%)
65-74	583 (7.1%)	8 (10.1%)	540 (5.7%)	12 (15.6%)
75+	1 013 (12.4%)	26 (32.9%)	484 (5.2%)	10 (13.0%)

4. Exposure, risk, and the relation between them

The relation between the number of accidents, risk and exposure was examined in study 1 (*paper I*). This study addresses the following research questions:

1. What is the relation between the volumes of pedestrians and bicyclists and the number of accidents for those road user groups?
2. How does the reliability and validity of safety performance functions vary owing to the length of observational periods concerning exposure?

4.1 Main results

The parsimonious models are shown in equations 8 to 11 (Ped. stands for pedestrians and M.veh. stands for motorized vehicles) and the statistical properties of the models in table 3. *N* represents the number of expected accidents per year, and *E* stands for exposure (number of pedestrian crossings | number of pedestrians | number of bicyclists per day | number of motorized vehicles per day). The parameters and statistical properties of the fully specified models are shown in table 3. Models i and ii (single accidents) are included only for comparison purposes, since the focus of this thesis is accidents between motorized vehicles and either pedestrians or bicyclists.

Equation 8	*Model i*	$N_{Ped.\ single} = e^{-5.992} \cdot E_{Ped.\ not\ crossing\ a\ street}^{0.589}$
Equation 9	*Model ii*	$N_{Bicyclists\ single} = e^{-7.282} \cdot E_{Bicyclists}^{0.676}$
Equation 10	*Model iii*	$N_{Ped.-M.veh.} = e^{-12.937} \cdot E_{Ped.\ crossings}^{0.554} \cdot E_{M.veh.}^{0.652}$
Equation 11	*Model iv*	$N_{Bicyclists-M.veh.} = e^{-11.273} \cdot E_{Bicycists.}^{0.427} \cdot E_{M.veh.}^{0.687}$

Table 3: Parameter estimations for the parsimonious base models. *This variable was included even though it was not statistically significant in order to maintain compatibility between models iii and iv and to examine the interaction between the parameters. **This value is estimated from comparable Poisson models (Kulmala, 1995), see Appendix A.

Variables	β_i	Standard error	p value
Model i: Single pedestrian accidents			
Intercept	-5.992	1.396	<0.001
Pedestrian flow	0.589	0.249	0.018
Pearson $\chi^2/df = 1.851$			
*Proportion of systematic variation explained: 0.421***			
Model ii: Single bicyclist accidents			
Intercept	-7.282	1.440	<0.001
Bicycle flow	0.676	0.201	0.001
Pearson $\chi^2/df = 0.879$			
*Proportion of systematic variation explained: 0.810***			
Model iii: Pedestrian – motorized vehicle accidents			
Intercept	-12.937	4.578	0.005
Pedestrian crossings	0.554	0.268	0.039
Motorized vehicle flow*	0.652	0.532	0.221
Pearson $\chi^2/df = 1.139$			
*Proportion of systematic variation explained: 0.943***			
Model iv: Bicyclist – motorized vehicle accidents			
Intercept	-11.273	2.454	<0.001
Bicyclist flow	0.427	0.175	0.014
Motorized vehicle flow	0.687	0.298	0.021
Pearson $\chi^2/df = 0.883$			
*Proportion of systematic variation explained: 0.703***			

For the parsimonious models, then, all primary exposure variables except flow of motorized vehicles ($p=0.221$) in the model for struck pedestrians (model iii, equation 10) were statistically significant ($p<0.05$). Despite this, the exposure of motorized vehicles was included in model iii (equation 10) to render model iii comparable to the model for accidents between bicyclists and motorized vehicles (model iv, equation 11).

To estimate the goodness of fit of the models we followed the methodology of Kulmala (1995), where comparable Poisson models with same set of variables were created and the degree of explained expected systematic variation[9] from those models were estimated[10]. Those Poisson models (see parameters of the Poisson models in Appendix A) explain between *43%* and *94%* of the expected systematic variation (see table 3). However, since those values are not based on the actual negative binomial models, they should only be considered an approximation. That the exposure alone (the parsimonious models) explains such a great proportion of the variance in the accident data is in agreement with prior studies (Fridstrøm et al., 1995; however, those studies where based on all accident types), though model iii shows very high degree of explained expected variation.

The parameters and statistical properties of the fully specified models are shown in table 4. Since the geometric variables were not statistically significant, it is not unexpected that those models showed poor statistical significance levels; only a few variables were statistically significant ($p<0.05$). Moreover, the Poisson models explain between *51%* and *104%* of the expected systematic variation, see table 4. They demonstrate a higher degree of explained variation than the parsimonious models do, but that is to be expected because including additional independent variables will usually result in a better statistical fit of the model. Observe that models ii and iii show an overfit, where they explain more than the systematic variation, i.e. the models are possibly also attributing part of the random variation to the variables. This might be due to inclusion of many geometric variables, and those models should therefore be considered unreliable.

The discussion regarding the exposure variables mainly focuses on the parsimonious models; the additional results are included mainly for comparison purposes, controlling to ensure that the observed effect in the parsimonious models is not simply a result of the omitted geometric variables.

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[9] The variation is often divided into two parts, (a) the random variation and (b) the systematic variation. The random variation cannot be predicted, nor can it be used to gain any understanding of the underlying reasons for traffic accidents. The systematic variation on the other hand is aimed at how the different variables influence the number of accidents.

[10] See Kulmala (1995) for details regarding the mathematical properties of this approach.

Table 4: Parameter estimations for the fully specific base models ($\boldsymbol{\beta_i}$). *The cities were grouped based on their geographical location. [1]*p<0.05,* [2] *p<0.10,* [3] *p<0.20*. Standard error of the models are shown in *paper I*. **This value is estimated from comparable Poisson models (Kulmala, 1995), see Appendix A.

	Variables	Model i	Model ii	Model iii	Model iv
	Intercept	-4.749[1]	-5.183[1]	-12.776[2]	-11.477[1]
Exposure variables	Pedestrian flow	0.434[3]		0.296	
	Bicyclist flow		0.371[3]		0.359[1]
	Motorized vehicle flow			0.644	0.712[2]
City*	Helsingborg/Kristianstad	0	0		
	Eskilstuna/Västerås	-1.137	-0.308		
	Kalmar/Halmstad	-1.469	0.269		
Traffic environment	Arterials		0.356	-0.479	
	Central		-0.060	-0.565	
	Rural/Industrial		-1.734[2]	-1.085	
	Residential		0	0	
Traffic control	Traffic signal		0.327	0.942	0.223
	Right of way/Yield/Stop sign		0	0	0
Speed limit	30-40 km/h			1.726	0.388
	50 km/h			1.219	0.596[3]
	60-70 km/h			0	0
Sight conditions	Good		-0.276		-0.432[3]
	Average/Poor		0		0
Bicyclist integration with car traffic	Fully integrated				0.471
	Partly integrated				0.163
	Fully segregated				0
	Pearson χ^2/df	1.778	0.870	1.371	0.839
	Proportion of systematic variation explained:**	0.514	1.015	1.044	0.785

4.1.1 The validity and reliability of accident models based on short observational periods

This study assumes that the base models (equations 8 to 11) are correct estimates. As already mentioned, this is not entirely accurate given that each exposure estimate is based on just three hours of observation, and it is possible that those three hours are not representative of the total flow at the accident site, or that they are not representative of the flow at the time of the accident, hence, creating an averaging problem[11] (Mensah and Hauer, 1998). Nevertheless, this approach allows one to compare the accuracy of the models based on shorter observational periods, and how much their estimates vary relative to the base models. Hence, I have tested the validity and reliability of the models based on shorter observational periods and compared them to the base models. In this way, it is possible to see whether a safety performance function based on short observational periods is likely to result in biased estimates of the model parameters compared to the true flows at the sites. Figure 19 shows how the parameters of the parsimonious models vary with observational period length for models iii and iv (a similar effect was observed for models i and ii, see *paper I*) and figure 20 shows how the parameters of the fully specified models vary with the observational period length for each model.

The parsimonious models based on short observational periods show considerable bias in the estimates of the parameters; hence, the models have lower validity than the base models do. Furthermore, the value for the parameters varies extensively between different datasets for the same length of observational periods, i.e. the reliability of models based on short observational periods is low. Had the model for accidents between motorized vehicles and pedestrians been based on 15 minutes of observations per site, the resulting parameter for the pedestrian flow might have been anywhere between about 0.20 and 0.46, compared to 0.55 for the base model. The same effect was observed for the fully specified models, see figure 20. Even though the estimates are in most cases within the 95% confidence interval of the model, this is important, since, had the study been based on the dataset where the parameter was 0.2, the

[11] Let us explain what is meant by averaging problem. One can hypothesize that the flow of importance for accident frequency is the flow at the time of the accident, where the greatest probability of an accident might be during peak flows, owing to high exposure; or during some other time, owing to behavioral aspects. Given the difficulty of measuring the flow at the time of the accident some average exposure is often used instead because it is not unlikely that that there will be some relation between the average exposure and the exposure at the time of the accident. However, exposure differs between different times of the day (for example differences in exposure between day and night), therefore, by using a mean exposure value for the day we might have lost part of the information (an average value is likely to reduce peak flows in the data and result in that we loose the information regarding that the composition of the exposure at each point in time, i.e. th composition of different road user might differ between periods), creating an averaging problem (Mensah and Hauer, 1998).

confidence intervals would have looked different, that might have influenced the conclusions.

The parameters used to compare the models show that the improvement of AIC and mean absolute residuals is marginal, while some improvement was observed for the *p* values of the parameters, however, the standard error actually became larger in most cases, see table 5 (page 56-57). Hence, the benefits of collecting 'better' data (by using longer observational periods per site) are not observed in the quality estimates. This is problematic since researchers often use those parameters to confirm that their model is valid. Researchers must therefore allocate more attention to confirming that their exposure estimate is accurate before they continue towards the statistical modelling process.

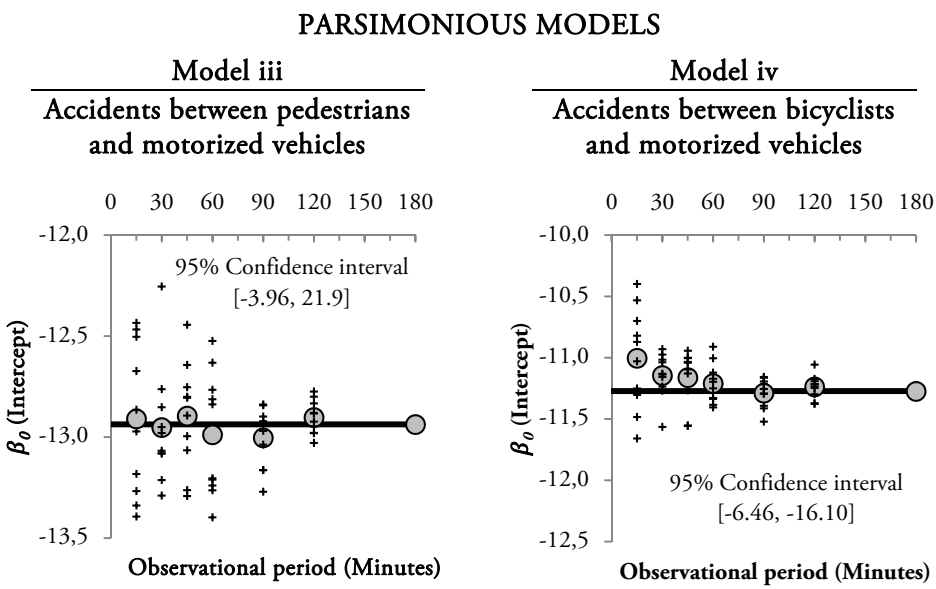

Figure 19: The parameters for the parsimonious models iii (equation 10) and iv (equation 11). Each cross represents one model, the circles are the mean of all models with that observational length, the black line represents the model parameter estimated for the base models and the grey lines show the confidence intervals for the parameters of the base model (*paper I*).

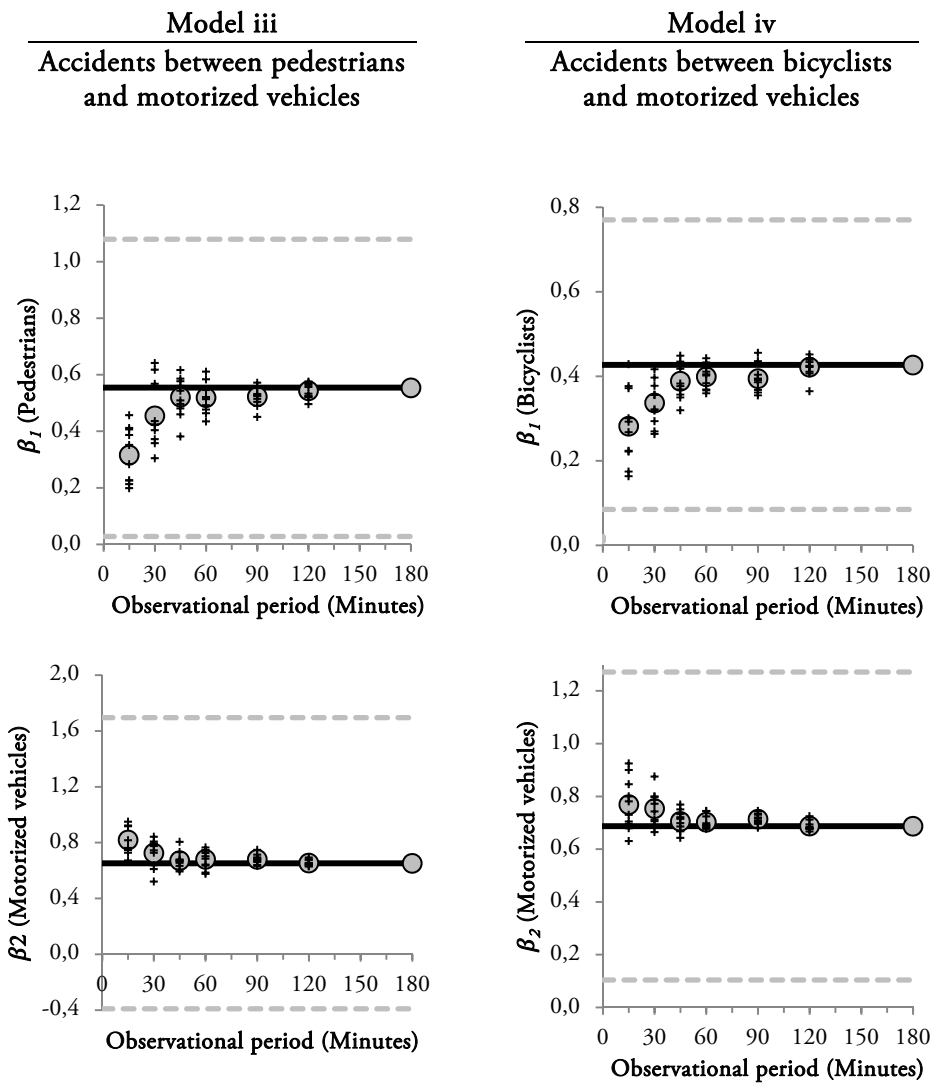

Figure 19 (continued): The parameters for the parsimonious models iii (equation 10) and iv (equation 11). Each cross represents one model, the circles are the mean of all models with that observational length, the black line represents the model parameter estimated for the base models and the grey lines show the confidence intervals for the parameters of the base model (*paper I*).

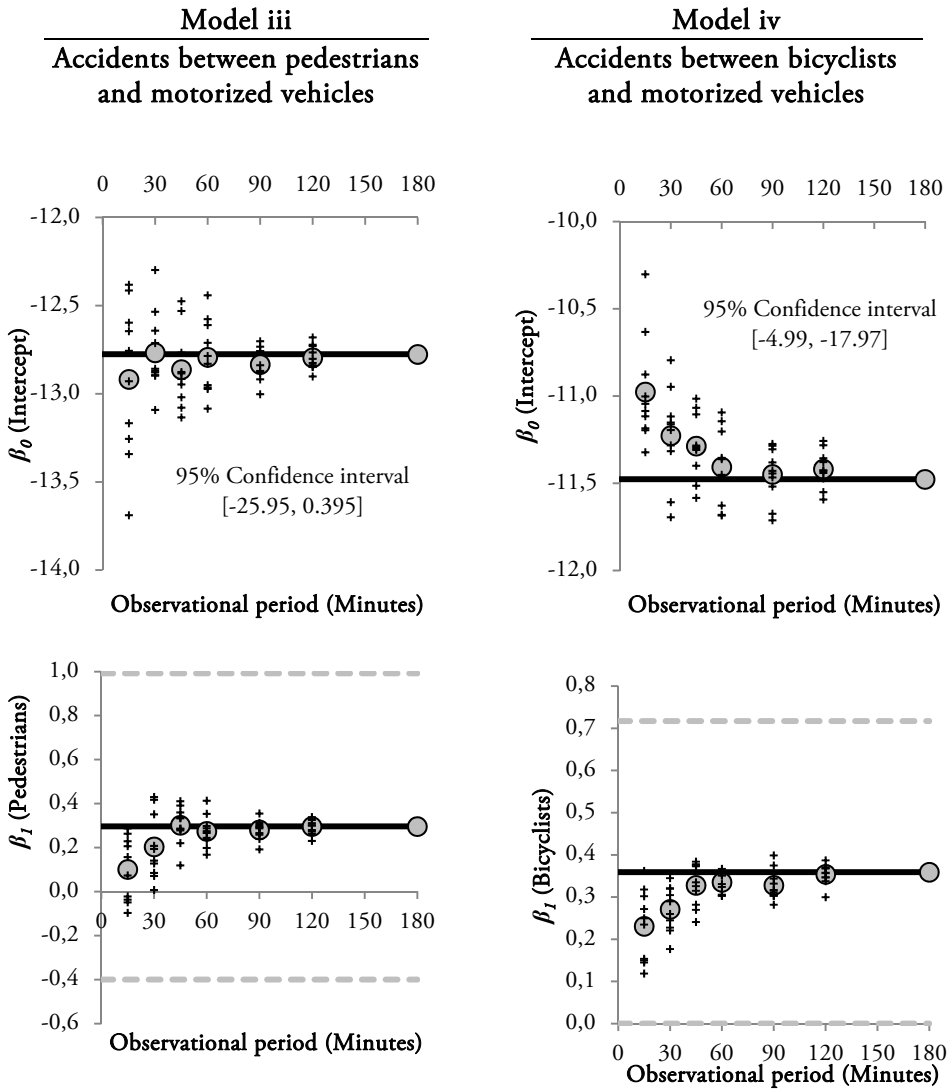

Figure 20: The parameters for the fully specified models iii (equation 10) and iv (equation 11). Each cross represents one model, the circles are the mean of all models with that observational length, the black line represents the model parameter estimated for the base models and the grey lines show the confidence intervals for the parameters of the base model.

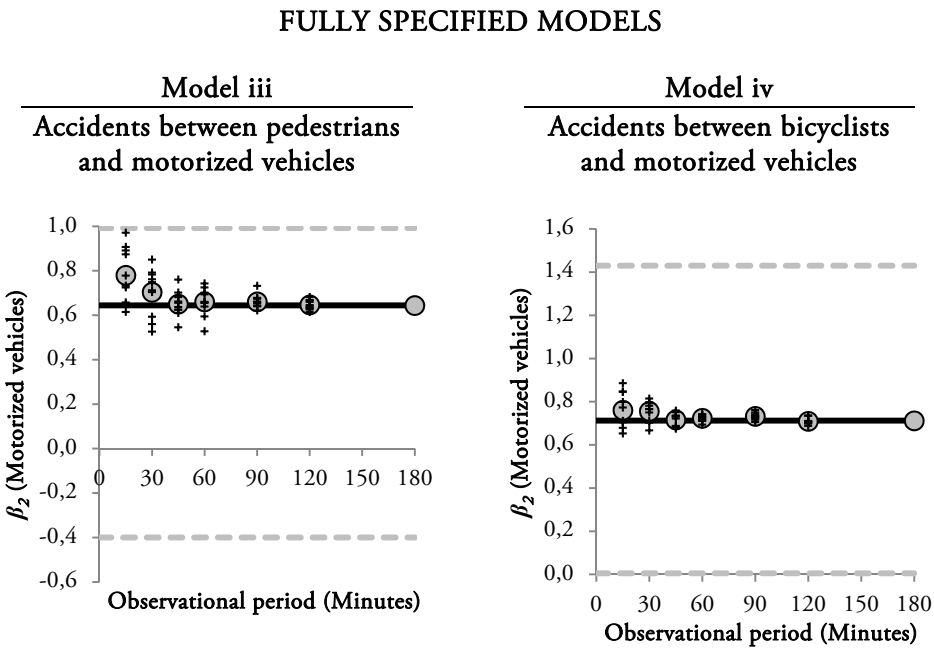

Figure 20 (continued): The parameters for the fully specified models iii (equation 10) and iv (equation 11). Each cross represents one model, the circles are the mean of all models with that observational length, the black line represents the model parameter estimated for the base models and the grey lines show the confidence intervals for the parameters of the base model.

Table 5: Statistical properties of the models based on different lengths of observational periods. Each value is a mean of the 10 models within that group of observational period length (*paper I*). Standard deviation is shown in parenthesis.

		Length of observational period (minutes)						
		15	**30**	**45**	**60**	**90**	**120**	**180**
Model i	β_0	-4.60	-5.49	-5.67	-5.88	-6.02	-5.97	-5.99
		(0.55)	(0.31)	(0.24)	(0.30)	(0.23)	(0.12)	
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	Standard error	0.80	1.12	1.19	1.30	1.39	1.37	1.40
		(0.14)	(0.07)	(0.09)	(0.13)	(0.12)	(0.05)	
	β_1	0.35	0.51	0.54	0.57	0.59	0.58	0.59
		(0.11)	(0.06)	(0.04)	(0.05)	(0.04)	(0.02)	
	p-value	0.025	0.013	0.012	0.014	0.015	0.016	0.018
		(0.016)	(0.009)	(0.005)	(0.002)	(0.002)	(0.001)	
	Standard error	0.15	0.20	0.21	0.23	0.25	0.24	0.25
		(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	
	AIC	130.69	127.56	128.05	127.70	127.48	128.10	128.71
		(6.01)	(2.40)	(2.00)	(1.75)	(1.22)	(0.85)	
	Absolute mean residuals	0.38	0.37	0.37	0.37	0.37	0.37	0.37
		(0.020)	(0.007)	(0.006)	(0.006)	(0.005)	(0.003)	
Model ii	β_0	-5.70	-6.47	-6.82	-6.74	-6.98	-7.00	-7.28
		(1.00)	(0.52)	(0.23)	(0.22)	(0.23)	(0.14)	
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	Standard error	1.13	1.28	1.35	1.34	1.38	1.40	1.44
		(0.17)	(0.08)	(0.06)	(0.03)	(0.02)	(0.03)	
	β_1	0.46	0.56	0.61	0.60	0.64	0.64	0.68
		(0.14)	(0.07)	(0.03)	(0.03)	(0.03)	(0.02)	
	p-value	0.014	0.002	0.001	0.001	0.001	0.001	0.001
		(0.027)	(0.001)	(0.001)	(0.001)	(0.001)	(<0.001)	
	Standard error	0.16	0.18	0.19	0.19	0.19	0.20	0.20
		(0.02)	(0.01)	(0.01)	(0.01)	(<0.01)	(<0.01)	
	AIC	173.63	172.66	171.87	172.29	171.87	171.99	171.18
		(3.93)	(2.05)	(1.24)	(1.04)	(1.00)	(0.46)	
	Absolute mean residuals	0.47	0.47	0.47	0.47	0.47	0.47	0,46
		(0.019)	(0.011)	(0.007)	(0.005)	(0.004)	(0.004)	

Table 5 (continued): See figure text on page 56.

		Length of observational period (minutes)						
		15	**30**	**45**	**60**	**90**	**120**	**180**
Model iii	β_0	-12.91 (0.38)	-12.95 (0.29)	-12.89 (0.27)	-12.99 (0.31)	-13.00 (0.15)	-12.90 (0.08)	-12,94
	p-value	0.008 (0.007)	0.006 (0.004)	0.005 (0.002)	0.004 (0.001)	0.004 (0.001)	0.005 (0.001)	0.005
	Standard error	4.76 (0.50)	4.61 (0.30)	4.54 (0.18)	4.55 (0.10)	4.54 (0.06)	4.55 (0.07)	4.58
	β_1	0.32 (0.10)	0.46 (0.11)	0.52 (0.07)	0.52 (0.05)	0.52 (0.04)	0.54 (0.03)	0,55
	p-value	0.157 (0.106)	0.084 (0.059)	0.050 (0.029)	0.048 (0.018)	0.043 (0.012)	0.042 (0.010)	0.039
	Standard error	0.21 (0.02)	0.25 (0.02)	0.26 (0.01)	0.26 (0.01)	0.26 (0.01)	0.27 (<0.01)	0.27
	β_2	0.82 (0.10)	0.73 (0.10)	0.67 (0.06)	0.68 (0.07)	0.68 (0.03)	0.65 (0.02)	0.65
	p-value	0.129 (0.044)	0.177 (0.058)	0.203 (0.033)	0.198 (0.047)	0.195 (0.027)	0.216 (0.013)	0.221
	Standard error	0.53 (0.05)	0.53 (0.03)	0.52 (0.02)	0.53 (0.01)	0.52 (0.01)	0.53 (0.01)	0.53
	AIC	113.42 (1.99)	112.40 (1.86)	111.68 (1.10)	111.89 (0.90)	111.90 (0.56)	111.73 (0.48)	111.67
	Absolute mean residuals	0.28 (0.005)	0.27 (0.008)	0.27 (0.005)	0.27 (0.004)	0.27 (0.003)	0.27 (0.001)	0.26
Model iv	β_0	-11.00 (0.41)	-11.14 (0.18)	-11.16 (0.22)	-11.21 (0.16)	-11.29 (0.12)	-11.24 (0.09)	-11.27
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	Standard error	2.43 (0.05)	2.45 (0.05)	2.44 (0.03)	2.44 (0.02)	2.45 (0.02)	2.44 (0.01)	2.45
	β_1	0.28 (0.09)	0.34 (0.05)	0.39 (0.04)	0.40 (0.03)	0.39 (0.03)	0.42 (0.02)	0.43
	p-value	0.034 (0.033)	0.034 (0.023)	0.019 (0.012)	0.015 (0.006)	0.019 (0.007)	0.014 (0.004)	0.014
	Standard error	0.11 (0.04)	0.15 (0.01)	0.16 (0.01)	0.16 (<0.01)	0.17 (<0.01)	0.17 (<0.01)	0.17
	β_2	0.77 (0.10)	0.75 (0.06)	0.71 (0.04)	0.70 (0.03)	0.71 (0.02)	0.69 (0.02)	0.69
	p-value	0.010 (0.008)	0.012 (0.006)	0.017 (0.005)	0.017 (0.005)	0.015 (0.003)	0.020 (0.004)	0.021
	Standard error	0.28 (0.01)	0.29 (0.01)	0.29 (0.01)	0.29 (0.01)	0.29 (<0.01)	0.30 (<0.01)	0.30
	AIC	255.70 (2.30)	256.09 (1.66)	255.31 (1.22)	255.07 (0.76)	255.59 (0.73)	255.04 (0.53)	255.15
	Absolute mean residuals	0.71 (0.02)	0.71 (0.01)	0.70 (0.01)	0.70 (0.01)	0.70 (0.005)	0.70 (0.01)	0.70

4.1.2 Reliability of exposure estimations

Even though the focus of this work was the influence of the length of an observational period on the safety performance functions, it is also interesting to study how that observation length influences the raw exposure numbers, i.e. how are the countings influenced by the length of the observational period. For this investigation, each individual observational period was used as one unit (i.e. all possible observational period lengths per site: 15, 30, 45 minutes observational periods per site).

Figures 21 to 23 show the relative ratio between exposure during the observational periods and the exposure based on 180 minutes of observations was (both values scaled to be average daily values), hence, the closer the ratio is to 1, the more accurate the estimated exposure is, based on the shorter observational period. The results show that the estimate usually improves when the observational period at the site is extended from 15 minutes, yielding, in essence, results similar to those for the accident models. At the same time, these results demonstrate that even though the observational periods are long, some of them have relative ratios upp till about 2. Hence, longer observational periods provides more reliable estimation of average exposure, but nevertheless, they should not be considered accurate, since there can still be a considerable measurement error.

Figures 24 to 26 shows the relative ratio between the exposure during 15 minutes of observations and the exposure during 180 minutes of observations (both values scaled to be average daily values, only 15 minutes of observations were used to avoid the issue that longer observational periods have higher exposure and better ratio due to that they are based on larger part of the 180 minutes of observations). Hence, if the observation provided an accurate estimate of the 180 minutes of observation, the relative ratio would be around 1 (located on the dotted line). The results show that the relative ratio is overall lower when the exposure is higher, i.e. the measurement error is lower if there is higher exposure during the observational period. This suggests that the observational period should not be based solely on a length of time but also on the degree of exposure; perhaps, the goal should be to reach some given degree of exposure and to estimate the daily values from the time it took to reach this amount of exposure, or to combine those approaches.

Neither of these approaches can be used to determine some absolute optimal length of an observational period per site. They can, however, aid researchers in determining the suitable length of observational periods for their studies based on how much uncertainty they accept.

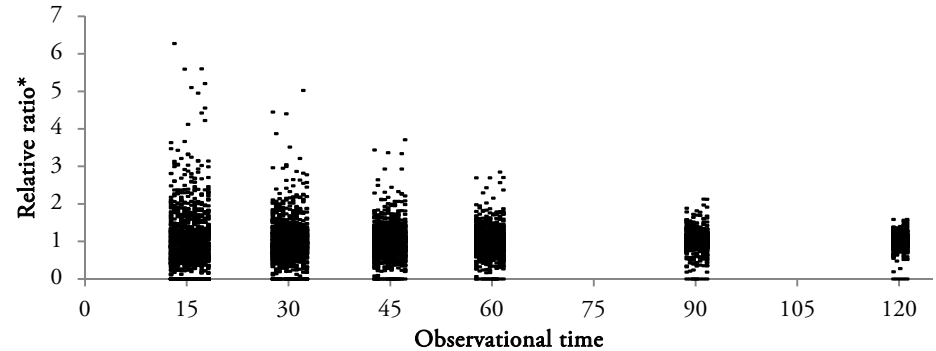

Figure 21: The relative ratio* for the exposure for the number of crossing by pedestrians during each observational period against the length of the observational period.

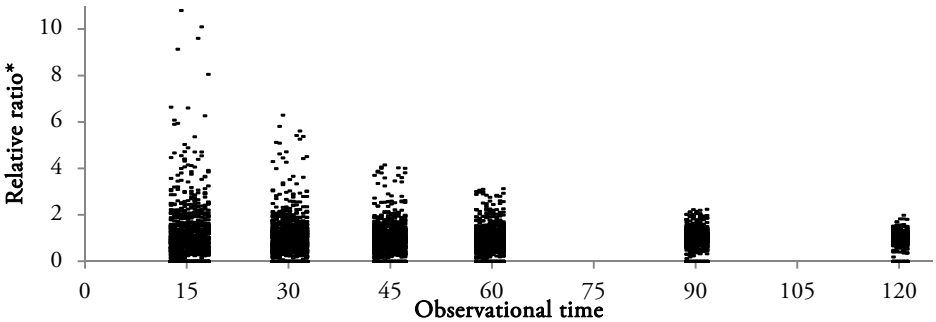

Figure 22: The relative ratio* for the exposure for the number of pedestrians entering the intersection without crossing a street each observational period against the length of the observational period.

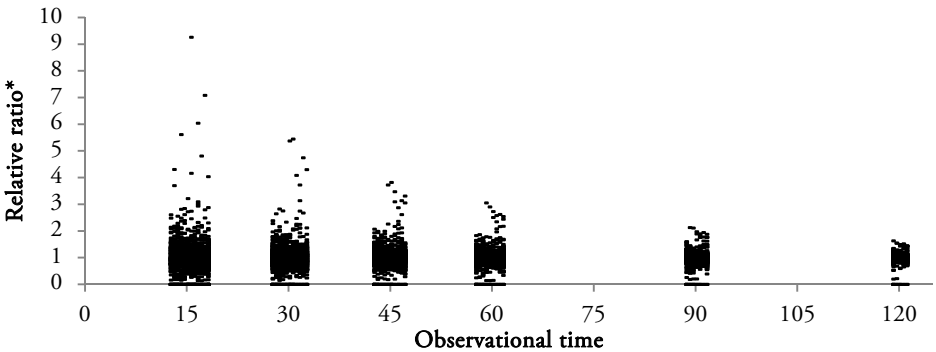

Figure 23: The relative ratio* for the exposure for the number of bicyclists each observational period against the length of the observational period.

* Relative ratio is exposure during the observation period (e.g. 15, 30, 45 minutes) divided by what is the average exposure according to the 180 minutes of observations, both scaled to be annual daily traffic. Each point represents one observation.

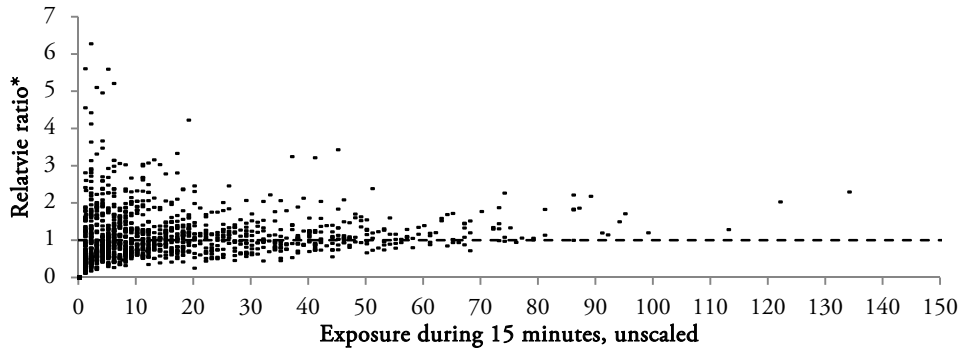

Figure 24: The exposure for the number of crossing by pedestrians during each observational period against relative ratio*.

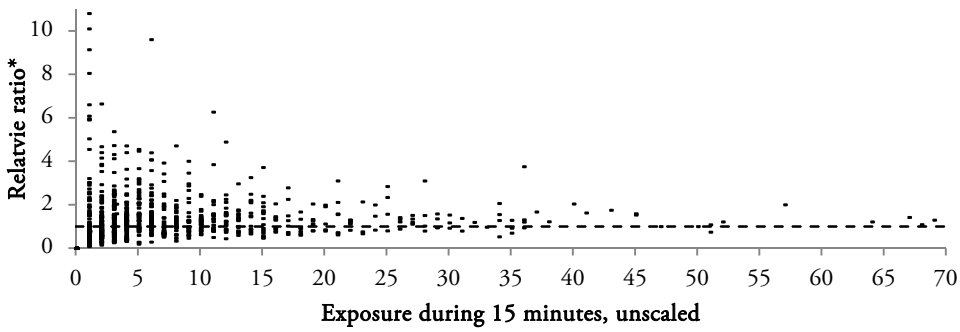

Figure 25: The exposure for the number of pedestrians entering the intersection without crossing a street during each observational period against relative ratio*.

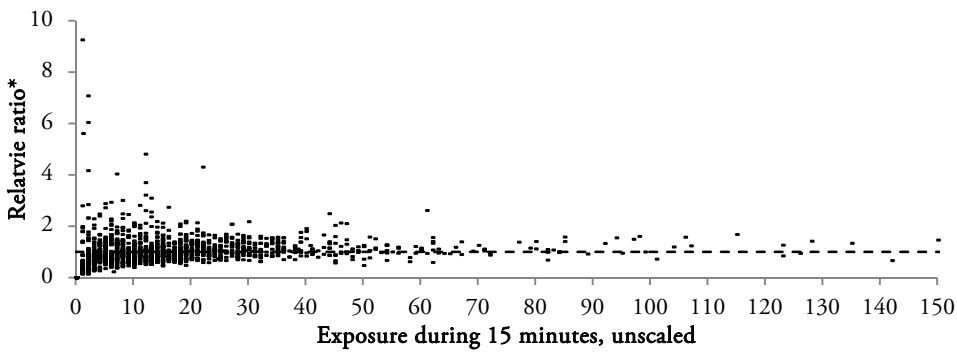

Figure 26: The exposure for the number of bicyclists during each observational against relative ratio*.

* Relative ratio is exposure during 15 minutes of observations divided by exposure during 180 minutes of observations, both scaled to annual daily traffic. Each point represents one observation.

4.2 Discussion

All the flow variables showed correlation with the number of accidents, i.e. the higher the exposure of pedestrians, bicyclists and/or motorized vehicles, the higher the number of accidents. This aligns with the findings of earlier studies (e.g. Brüde and Larsson, 1993, Elvik, 2009a). The models furthermore show that the exponent of the exposure variables is below 1.0. This non-linear correlation suggests that (a) the number of collisions between pedestrians, bicyclists and motorized vehicles does not increase proportionally with the increase of the exposure of pedestrians, bicyclists and/or motorized vehicles, reflecting a phenomenon, frequently referred to as safety in numbers; and (b) the number of accident involving pedestrians and bicyclists increases with greater exposure of motorized vehicles, even if the exposure of pedestrians and bicyclists is kept unchanged. This is illustrated in figures 27 and 28. Observe, though, that at individual sites, the relation between traffic flow and the number of accidents might be more complex. It is possible that the individual intersection will have some sweat point (regarding exposure) at which the intersection functions at optimum from safety perspective.

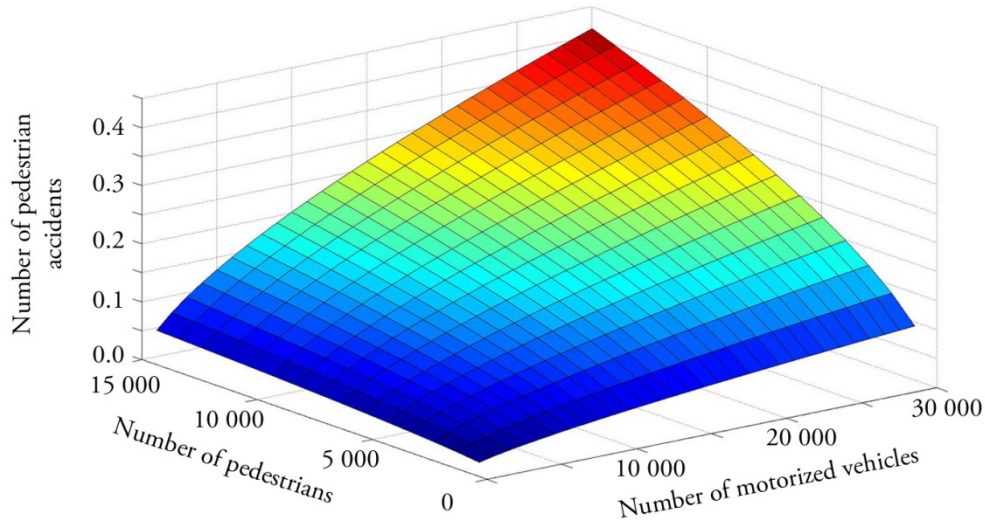

Figure 27: Three dimensional graph illustrating how the number of accidents between pedestrians and motorized vehicles (accidents per year) relates to the flow of pedestrians and motorized vehicles according to model iii (equations 10).

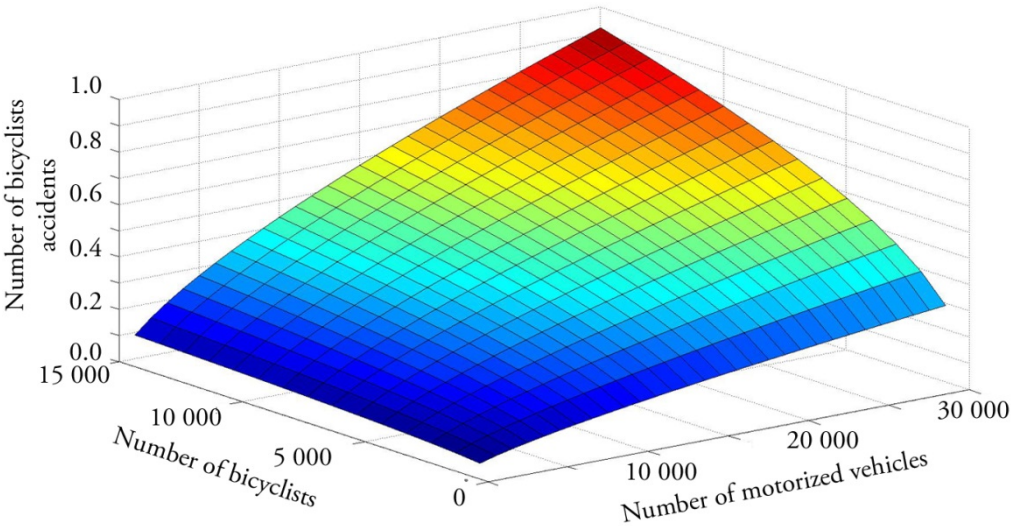

Figure 28: Three dimensional graph illustrating how the number of accidents between bicyclists and motorized vehicles (accidents per year) relates to the flow of bicyclists and motorized vehicles according to model iv (equation 11).

4.2.1 Safety in numbers

The fact, that the number of pedestrian and bicyclist accidents increases with increased exposure of motorized traffic is probably because an increase in the volume of motorized vehicles increases the probability of interaction between those two road user groups; interaction, again, which is ultimately required for an accident to occur. It might be suggested that this relation should not be non-linear, and that the exponent should be forced to 1.0, approach that assumes that the risk per road user should be constant independent of the level of exposure. There are, however, indications, or at least theories, that the risk per road user is not independent of the exposure level, suggesting that this kind of constraint might constitute a questionable approach. Several earlier studies have found this nonlinearity in the relation (e.g. Brüde and Larsson, 1993, Elvik, 2009a, Leden, 2002) and there are several theories regarding why the models do not show the number of pedestrian and bicyclist accidents increasing proportionally alongside the exposure of pedestrians, bicyclists, and motorized vehicles. Even though most of those studies have focused on explaining the safety in numbers effect for pedestrians and bicyclists, it is reasonable to expect that the reasons they outline would also apply, at least partly, to a safety in numbers effect for drivers of motorized vehicles. The most frequent theories are these:

(1) Higher exposure of pedestrians and bicyclists makes the drivers of motorized vehicles more aware of the possibility that pedestrians and bicyclists might be present (awareness and expectations), which might result in more careful

driving, i.e. a behavioral adaptation that decreases the risk of collision (e.g. Ekman, 1996, Jacobsen, 2003, Jonsson, 2013). Similarly, higher traffic volumes of motorized vehicles might increase awareness among pedestrians and bicyclists, resulting in safer behavior and explaining why the models observe an safety in numbers effect for motorized vehicles.

(2) More travelling as a pedestrian, bicyclists and/or user of a motorized vehicle might allow indiciduals to acquire skills that result in lower accident risk (Elvik, 2015).

(3) There might be a complex relation between the number of road users (exposure) and the probability of an interaction between a pedestrian or a bicyclist and a motorized vehicle occurring (Elvik et al., 2009); or due to how great the exposure is during peak hour. Hence, the *risk ~ exposure* relation might be more linear if exposure were expressed in number of interactions instead of number of road users. It is also not possible to exclude the possibility that this effect owes to the use of an average estimate of exposure (instead of using the exposure at the time of the accident).

(4) Some other undiscovered mechanism behind this that correlates with both exposure and risk. This include the possibilities that the relation is not safety in numbers, but rather numbers in safety, hence, that road users choose traffic environment that are safer (Bhatia and Wier, 2011), hence, creating a correlation. Also, if the model is based on ratio variables, then this might be partly a statistical phenomenon or spurious correlation (Brindle, 1994, Elvik, 2013a).

(5) Higher exposure of pedestrians, bicyclists and motorized vehicles might correlate with better infrastructure and maintenance, resulting in lower accident risk at locations with high exposure (Brüde and Larsson, 1993, Jonsson, 2013, Schepers, 2012). That is, the exposure variable is working as a proxy for the quality of the infrastructure.

Many studies emphasize the first explanation (e.g. Jacobsen, 2003). But one can speculate that all five explanations are contributory, questioning whether it is possible to draw the firm conclusion that a causal relation exists (Bhatia and Wier, 2011). My results do not allow for a determination of which explanation contributes most to this effect, but comparable models for single accidents facilitate brief reflections on these ideas.

If the first theory is accurate, one might expect that a safety in numbers effect would be observed for the accidents involving motorized vehicles (models iii and iv). It is even possible that this effect would be observed in single bicycle accidents (model ii). The existence of more cyclists might influence awareness and behavior at the same time as more cycling in general might increase bicyclists´ skills, experience, and knowledge of dangerous locations (the second theory), resulting in reduced risk per

bicyclist. However, it is unexpected that a safety in numbers effect is observed for single pedestrian accidents. One would not expect to see pedestrians changing their behavior so that there are fewer single pedestrian accidents because there are more pedestrians; even though the possibility, that the presence of more pedestrians might indicate that people walk more, resulting in greater skill and thus lowers the risk of single accidents cannot be excluded (the second theory). The third theory might influence models iii and iv (equations 10 and 11), but it is not relevant for the single accident models (models i and ii), which show a safety in numbers effect similar to that in the models for collisions with motorized vehicles (models iii and iv). The fourth theory is likely part of the explanation. Accidents are extremely complex occurrences and it is unlikely that we fully understand this relation. It is possible that this effect is influenced by the type of pedestrians or bicyclists who are travelling in various locations (e.g. experienced bicyclists may be overrepresented at locations where exposure is high, possibly introducing bias into the analysis). The fifth theory, that the safety in numbers effect owes to correlation between exposure, quality of infrastructure, and quality of maintenance (i.e. that exposure is partly working as a proxy variable for the infrastructure´s quality) must be considered highly probable to contribute to this effect, and since it is also possible that the quality of the infrastructure is more closely related to the exposure of motorized vehicles, this might partly explain the safety in numbers effect for that road user group. Improved infrastructure reduces the risk of an accident occurring (e.g. Elvik and Vaa, 2004), and it is likely that municipalities focus on providing good level of service, safe infrastructure and good maintenance at locations where exposure is high. This would result in a correlative relation in which the number of accidents does not increase proportionally as fast as the number of pedestrians and bicyclists. This might be part of the explanation for the safety in numbers effect of the single accidents. If this correlation is part of the explanation for the single accident models, one might wonder how important this factor is for the other accident types (models iii and iv). Given that in the fully specified models, the geometric variables had considerable influence on the exponents for exposure, it is likely that theory 5 is part of the explanation. Finally, it is possible that the applicability of these five possible explanations differs between accident types. The data and models here cannot determine which assumption is the most important one; this requires further studies to determine the contribution each makes to the safety in numbers effect.

Elvik and Bjørnskau (2014) concluded from a literature study that it was likely that the safety in numbers effect is real, since the different studies are highly consistent; they however concluded that it is not possible at this stage to determine if the safety in numbers effect is in fact causal or simply a correlative relation. Recently, there have been some attempts to investigate the mechanisms behind the safety in numbers effect for cyclists (de Goede et al., 2014, Fyhri and Bjørnskau, 2013), by investigating the number of conflicts and encounters between two/three time periods (with different level of exposure) at the same location. De Goede et al. (2014), based on one

intersection, did not identify any substantial differences in conflicts between two time periods. Fyhri and Bjørnskau (2013) however found some differences regarding the mean time a cyclists had experienced poor interaction with car users between three time periods. However, since those studies (or this part of the studies) was only based on one and three intersection, and it is possible that the composition of cyclists (and other contributory facors, etc. weather) might influence the comparison, no firm conclusion can be drawn from this.

It is also important to emphasize that models such as those presented here do not necessary indicate that increasing the volume of exposure at a given location will result in lower risk per road user (Kulmala, 1995). This would require that the safety in numbers effect is causal, but it remains to determine how great the contribution of the different theories (discussed before, some of which are causal, while other are not) is to the safety in numbers effect.

4.2.2 Validity and reliability of models based on short observational periods

The parameters of the models based on short observational periods per site differed somewhat from the base model. Those results where in line with the conclusions from Maher and Summersgill (1996, pp. 293-294):

> *"(a) Randomizing one flow variable leads to a bias (underestimate) in its coefficient. (b) Randomizing one variable has a small but non-zero "cross-over" effect leading to a bias in the coefficient associated with other flow variables. (c) The effect of randomizing two variables simultaneously is the sum of the two separate effects"*

Even though this was in most cases within the confidence intervals of the base model, this measurement error is of importance, for several reasons. (1) The models are often used as prediction models or as a statistical model for research purposes. In that case, it is often the estimated parameter that is used, therefore, the measurement error will influence the use of the model. (2) Had the study been based on 15 minutes of observations per site, then it could have resulted in any of the models in figure 19. Even though the confidence interval of those models would most likely include the parameter estimation of the base model, then, if the model had been the one that results in parameter estimation far from the base model, it would be located in the outer parts of the confidence interval, and the confidence interval of this model (i.e. the one with short observational period) might, for example overlap over zero or one, hence, influence what conclusions will be drawn from the model; but from that model, the researcher has no knowledge of what the confidence intervals of the base model might be. It is therefore important for researchers, and practitioners that use those models, to realize that measurement error can influence the models, and that,

according to my results, this will not be obvious from the statistical parameters frequently used to estimate the model, such as standard errors, AIC etc. It is therefore important that researchers, and modelbuilders, in advanced, weigh the advantages of including many sites against the reliability of the estimation of the exposure, hence the measurement error.

4.2.3 Limitations

This study has some limitations, that need to be acknowledged.

(1) All accident databases are subject to underreporting, especially in the realm of single accidents. Higher degrees of underreporting for single accidents would influence the safety performance functions, that is, the actual risk would be higher than the one presented by the models. This would even influence the comparison between models for single accidents and those for accidents involving motorized vehicles. The degree of underreporting relates to injury severity, as well (Elvik and Mysen, 1999), and might differ according to location (for example distance to a hospital). This might influence the accident models and perhaps also the safety in numbers effect.

(2) The models describe the relation between daily exposure and accident risk. The exposure quantities are based on counting, and the traffic volumes for pedestrians and bicyclists are based on only 180 minutes of observation per site. It is possible that the results would have been different if long term counting had been conducted in order to gain a more valid estimate of daily exposure, but traffic volumes vary across time periods, days, and years. (Esawey et al., 2013). In addition, this study excluded peak hours from the observations, a choice that may have influenced the estimate of daily exposure.

(3) The use of daily exposure can be questioned (Mensah and Hauer, 1998). One might argue that perhaps it is the exposure at the time of the accident that is most important, especially if the explanation for the safety in numbers effect is awareness of other road users. Moreover, the relation between risk per road user and exposure is probabilistic in its nature (partly a proxy relation). A more direct approach might be to define exposure in terms of the number of interactions between motorized vehicles and pedestrians or bicyclists (Elvik, 2014a).

(4) The model for single pedestrian accidents uses the exposure variable of number of pedestrians entering the intersection without crossing a street. A better approach would have been to use all pedestrians who entered the intersection, since pedestrians who do cross a street may also be involved in single pedestrian accidents. Unfortunately, the data could not be used to determine how many pedestrians were behind the number of times a pedestrian crossed a street (a single pedestrian can cross more than one street). However, those two variables are correlated (*correlation* =

0.477), and using the number of pedestrians entering the intersection without crossing a street should be acceptable for the purposes of this study (even though this can be expected to influence the model).

(5) The safety performance functions did not show the geometrical variables to be statistically significant, but infrastructure is highly important for accident risk (Elvik and Vaa, 2004); therefore, this lack of significance might influence the safety performance functions and the relation between risk and exposure. The failure to reflect significance might owe to large standard errors stemming from low number of sites in the study, but obtaining statistically significant parameters for safety effects often requires large datasets (Kulmala, 1995). To counteract for this limitation, two parallel approaches were applied, and geometric variables were included based on sensitivity analysis. Both approaches showed similar effects, even though the estimate of the exposure parameters differed somewhat.

(6) This study is based on intersections in Sweden. The traffic situation is constantly changing and may vary between regions and countries. Therefore, it is not possible to provide an absolute recommended time for observations; I can offer only an estimate of how one can expect the reliability and validity to vary according to the length of observational periods.

(7) Finally, cross sectional studies can identify correlation between variables, but caution is in order when using cross sectional studies and statistical models to determine whether an effect is in fact causal or is simply a correlation (Elvik, 2011, Hauer, 2010).

4.3 Concluding remarks

There is a strong correlation between exposure and number of accidents whereby the number of collisions between pedestrians and motorized vehicles and between bicyclists and motorized vehicles increases proportionally faster than the exposure of pedestrians, bicyclists, and/or motorized vehicles does.

The results show that basing exposure variables for the safety performance functions on short observational periods can result in low reliability and validity of the models, even though it was within the confidence intervals of the models. For these data, a good suggestion might have been to collect data for about 45 minutes per site (even though this also involves some measurement error). But even data collected this way might not be fully transferable to other conditions or other countries.

Since collecting data about exposure demands significant resources, researchers must often weigh (a) on one hand, the benefits of including many sites in a study, which might allow for the inclusion and control of many geometrical variables, even though

limited resources may dictate short observational periods per site, against, on the other hand (b) the reliability of the method for determining exposure, where greater reliability requires longer observational periods per site. The researcher must, however, be aware that the quality of the exposure estimate might not be apparent from the model´s statistical properties. The validity of the exposure estimate should be estimated separately from the modelling process.

Finally, safety performance functions for single pedestrian accidents (and single bicyclist accidents) show a safety in numbers effect. This might suggest that the underlying reasons for this effect is more complex than previously assumed.

5. The consequence dimension

The consequence dimension was investigated in study 2 (*papers II, III* and *IV*), which adressed the following research questions:

3. How to interpret the relation between impact speed and injury level of pedestrians struck by motorized vehicles, and what are the implications for speed policy?
4. What is the relation between the speed environment at the accident site and the injury severity/outcome for pedestrians and bicyclists struck by motorized vehicles?
5. What is the relation between the age of the victim and the injury severity/outcome of pedestrians and bicyclists struck by motorized vehicles?
6. What are the differences in injury severity/outcome for pedestrians and bicyclists, struck by motorized vehicles?

5.1 How does impact speed influence the injury level of struck pedestrians?

In Sweden, it has been a common practice to use one (or more) of three fatality risk curves to describe the relation between the probability of fatality for pedestrians struck by motorized vehicles and the impact speed. Those curves show the fatality risk increasing steeply after 30 or 40 km/h (Anderson et al., 1997, Pasanen, 1992, Teichgräber, 1983). Those curves were based on data from England, collected during the periods 1966-1968, 1973-1976, and 1976-1979 (Ashton, 1980); from Switzerland, collected in 1978, 1979 and 1981 (Walz et al., 1983, Walz et al., 1986); and from the American state of Florida, collected during the period 1958-1963 (Yaksich, 1964). Two of those datasets (Ashton, 1980, Walz et al., 1983, Walz et al., 1986) were collected using an outcome based sampling strategy, and the underrepresentation of non-fatal accidents was high (Davis, 2001, Rosén and Sander, 2009). Since the authors of those studies (Anderson et al., 1997, Pasanen, 1992) did not intend to investigate the absolute injury risk but rather to use it as a step in their work to estimate the relative fatality risk, this was not as problematic; the relative

approach reduces the influence of the bias created by outcome based sampling (see discussion regarding how underreporting influences relative risk in *paper II*). Later on, however, those curves were used separately as absolute fatality risk curves (e.g. Johansson and Linderholm, 2008); in this role they are not representative, and they greatly overestimate the risk of fatality. The third dataset, from Yaksich (1964), was based on accidents that occurred within an area that had an unusually high proportion of senior inhabitants, but the focus of that study was on seniors in traffic accidents. Seniors have an elevated risk of fatality compared to younger pedestrians (e.g. Davis, 2001, Tefft, 2011). In addition, the dataset is over 50 years old and can therefore hardly be expected to be representative of the current population, health care, or the vehicle fleet. It can therefore be stated that none of those curves are suitable for use today. However, since those curves have been used so widely to understand and to describe the importance of impact speed for injury outcome and to determine suitable speed limits, that the implications of this fact, that the validity of those fatality risk curves is low require consideration.

A comprehensive literature search was performed to identify the most reliable studies describing the relation between a pedestrian´s fatality risk and the impact speed in collisions with motorized vehicles. Most studies applied outcome based sampling without taking its limitations into consideration during the analysis (e.g. Anderson et al., 1997, Oh et al., 2008, see complete list in *paper II*). This resulted in inaccurate estimates of the fatality risk; hence, those studies are not reliable for this purpose. The literature review identified six fatality risk curves that were based on valid methodology (Kong and Yang, 2010, Richards, 2010, Rosén et al., 2009, Rosén and Sander, 2009, Tefft, 2011), Each of those studies had its own criteria for including accidents into the study (and hence excluded certain age groups or certain vehicle types) and its own sets of limitations, listed in *paper II*.

The fatality risk values, from those studies, for impact speed of 30, 50, and 70 km/h are shown in figure 29, which demonstrates that the fatality risk varies extensively between studies. At the impact speed of 30 km/h, the risk ranges between 0.6% (Richards, 2010) to 5.8% (Tefft, 2011), at 50 km/h, from 6.3% (Rosén et al., 2009) to 25.6% (Kong and Yang, 2010) and at 70 km/h, from 31.4% (Rosén et al., 2009) to 82% (Kong and Yang, 2010). Such great variation demonstrates that the findings in the literature cannot be used to determine some 'universal' fatality risk for a given impact speed.

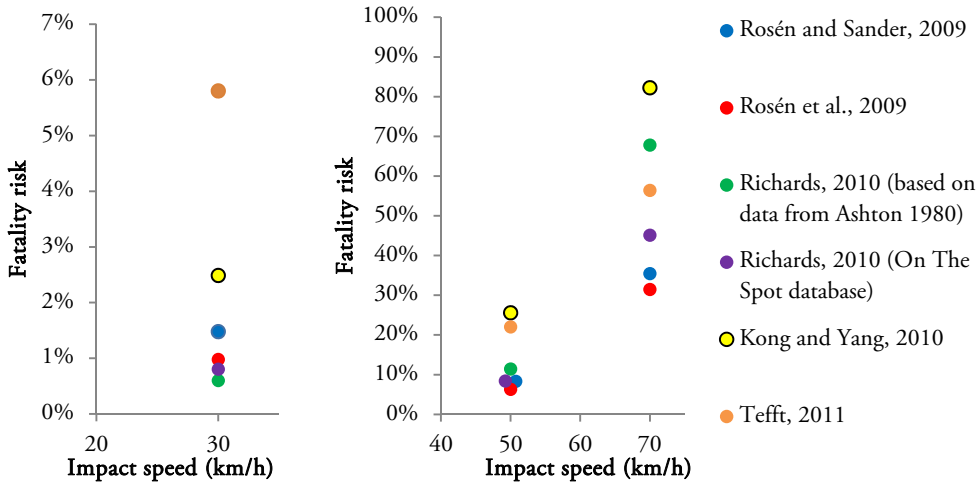

Figure 29: Overview of fatality risk estimations for impact speed in several studies (*paper II*)

At first glance, it might seem strange that the fatality risk should vary so extensively between studies. However, there can be many natural reasons for this variation. Each study has its own inclusion criteria, and the population a study is based on varies based on where and when the study was performed. The fatality risk is strongly influenced by the victim´s age (e.g. Henary et al., 2006), the vehicle type (e.g. Desapryah et al., 2010), and not least the reporting degree in the region (Elvik and Mysen, 1999). Given these differences, it is not unexpected that the fatality risk varies so greatly between different studies. This variation is probably not due to that the curves are ´wrong´ (though they certainly have their limitations); rather, they apply to different populations. This should lead one to question the method of blindly applying a fatality risk curve from one country or region to another.

It is also necessary to be aware of the limitations of the injury risk curves. No model is better than the data it is based on, and the fatality risk curves are subject to measurement errors (Kullgren and Lie, 1998; Rosén and Sander, 2010) that can result in an underestimation of the fatality risk at higher speeds. Moreover, the studies are mainly based on accidents that occurred in urban speed environments; hence, the fatality risk curves should not be applied for higher speeds. Finally, all those curves rely on the assumption that fatality risk has an S shape. One can discuss whether this is a proper form for the fatality risk curve, arguing that other forms are possible. Sadly, the data is limited; hence, it is hard to empirically determine the real shape of the fatality risk curve, especially its upper part. The question can, however, be approached theoretically, as was done in *paper II* (with the caution that the findings require empirical confirmation).

Let us assume that each individual has some theoretical speed tolerance threshold; if the impact speed is below this threshold, he or she will survive; otherwise he or she will die. For the fatality risk curve to be linear, the group that has a very low speed threshold must be the same size as the group with a mean threshold (see figure 30). For the curve to be exponential or to have a power function, the group with the highest speed threshold must be the largest group, and then at a higher speed no one would survive. It must be considered unlikely that either of those situation is the case. Those who have a very low or a very high speed tolerance threshold can be expected to be exceptions, whereas the majority has a speed tolerance threshold somewhere in the middle, yielding some kind of normal distribution. This would result in a fatality risk curve with an S shape (see figure 30). Therefore, we can speculate that the S shape is the most likely form for the fatality risk curve. Nevertheless, no empirical data were found that could be used to test the upper part of the curve, nor is it possible to exclude the possibility that the curve is not symmetrical or that it is influenced by the fact that different parts of the body have different tolerance levels for injuries (Walz et al., 1986). Therefore, the S shape is the best choice available until some empirical support emerges for using another form. Owing to those

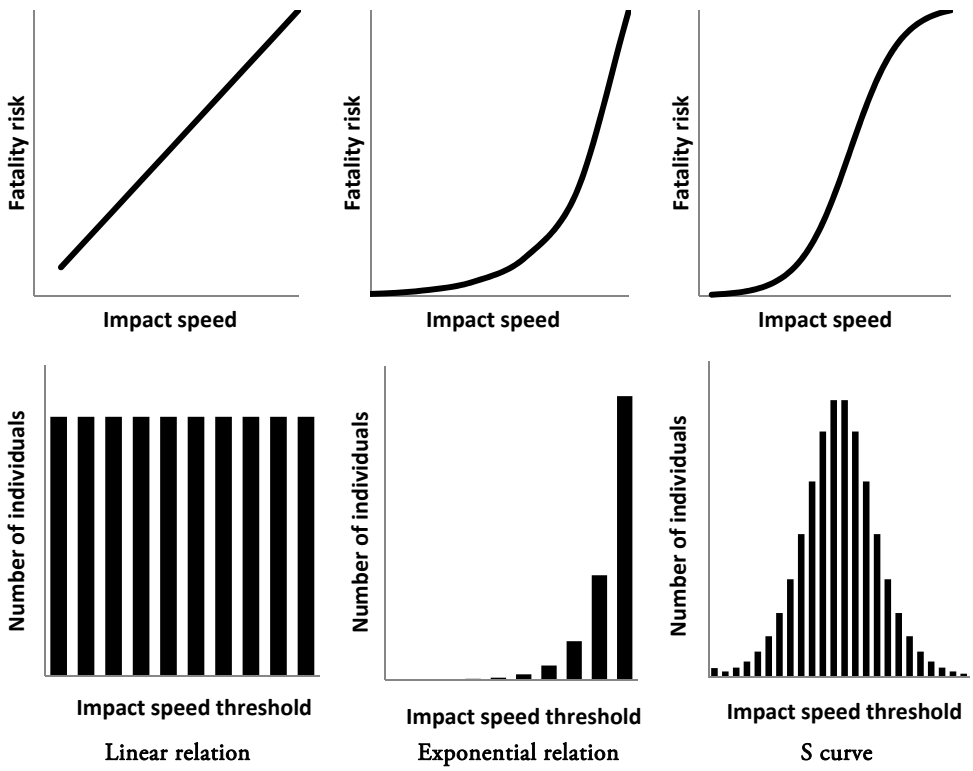

Figure 30: Theoretical forms of fatality risk curve.

uncertainties (and other limitations), however, the fatality risk curve and all models based on those curves should be considered imperfect guides to better understand the relations and how speed influences traffic safety.

5.1.1 Why have the fatality risk curves changed so drastically?

Figure 31 shows one of the earlier curves (Pasanen, 1992) and one of the more valid curves, based on recent data (Rosén and Sander, 2009). It is obvious that they differ considerably. Pasanen (1992) showed the steepest increase in fatality risk occurring after 30 to 40 km/h, while Rosén and Sander (2009) showed it occuring after 50 to 60 km/h. The old curve is unreliable because it was not weighted and relied on an outcome based sample (Ashton, 1978). However, Richards (2010) used the same data to analyze this relation and weighted for the bias caused by the outcome based sampling strategy. Those weighted fatality risk values show the new curve to involve similar fatality risk values at urban speeds.

Even though there are several confounding factors that might complicate this comparison (such as composition of the population), there is no evidence in the accident data that the fatality risk is substantially lower at urban speeds than before. The high fatality risk in the earlier curve emerged mostly because the data were biased.

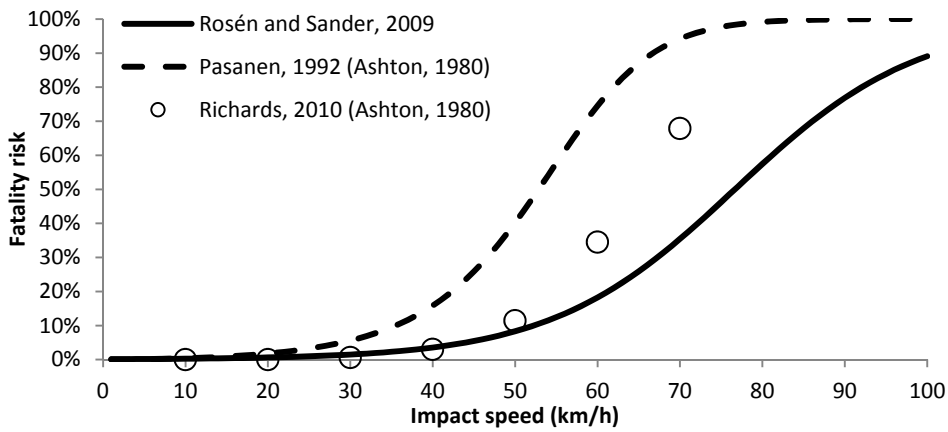

Figure 31: One of the earlier fatality risk curves, scaled values of that curve and one of the newer fatality risk curves. All values are for pedestrians struck by motorized vehicles.

5.1.2 What does this mean? Is speed not a safety issue at urban speeds?

The fatality risk curves (and S curves in general) give the visual impression that the most *critical speed* is found at the point where the steepest increase starts and that this is the speed that should not be exceeded, while there may be little to gain from speeds lower than this. ***Before we go any further, let us emphasize that this is a visual problem;*** zooming in on the low speeds makes it apparent that the fatality risk is increasing exponentially even at low speeds (Rosén and Sander, 2009).

There are several ways to interpret these results. The individual road user might have some perceived maximum acceptable risk that he or she will consider trivial; hence the acceptable speed would be the one where the risk of fatality (or serious injuries) is below this threshold. The individual would also probably consider that tripling the risk from 20% to 60% is much less desirable than tripling it from 2% to 6%, hence, the former speed change is 'critical' while the latter is more 'trivial'. From the individual's perspective, the steepest part of the curve is probably perceived as most important, supporting the interpretation of critical speed. Hereafter, I refer to this viewpoint as the *individual perspective* in interpreting those results.

The individual perspective, faces some challenges. (1) The risk of fatality is generally low if one is struck by a motorized vehicle. It may be difficult for individuals to perceive how important the risk change from 2.5% to 3% is. (2) The literature reveals that the absolute fatality risk values vary between studies, furthermore, underreporting makes it impossible to determine the real fatality risk (the most reliable studies have indicated that the fatality risk lies somewhere between 6.3% and 25.6% at an impact speed of 50 km/h, and even those studies are subjected to underreporting). Therefore, the individuals, and those applying the individual perspective for speed policy purpose, have no basis on which to determine the critical speed that fits the individuals accepted risk level. (3) The speed policy must be for all road users, but since each individual might have his or her own accepted risk threshold, it is difficult to identify an appropriate speed that will fulfill the needs of all road users. (4) The fatality risk will differ depending on vehicle type, accident mechanisms, and age of the victim. Davis (2001) showed that even though the critical speed was about 50 to 60 km/h for adults, it was at much lower speeds for seniors (60+), near 30 to 40 km/h. (5) If one says, for the sake of argument, that the absolute fatality risk has been decreased, then the new fatality risk values would have resulted in fewer fatal accidents today; in other words, the reduction would have already resulted in a decreased number of fatalities. If we change the speed to reach some prior absolute fatality risk, that would again lead to an increased number of fatal accidents. Is it acceptable to increase the speed to reflect the acceptable risk level for individuals if we know that doing so will most likely result in more fatalities?

A second perspective for interpreting risk curves for speed policies is that even though the loss caused by an accident always occurs on an individual level, it may be more

appropriate to approach the matter from a *system perspective*, that is, by considering the influence of speed on society as a whole. While an individual might not perceive the importance of fatality risk increase from 2.5% to 3% (a relative risk of 1.2), a 20% increase in the number of fatalities would certainly be important for the society as whole. This approach has the advantage of considering how changes in speeds might influence the number of fatal accidents and does not assume that there is some acceptable risk of fatality, and since it is relative, it avoids the issue of our inability to accurately determine the absolute fatality risk accurately. The disadvantage of this approach, however, is that it does not allow for the determination of an absolute acceptable speed for speed policy purposes; rather, it indicates how much could be gained or lost by changing the impact speed (through speed policy).

The third perspective is *the number of accidents perspective*. Every fatality (or serious injury) is important. Therefore, when considering how the number of accidents can be changed through influencing the speed, one consideration should be how we can save the most lives. Changing the speed might not be effective in a place where there are no fatal accidents (owing to the combined effects of low exposure, low risk of an accident occurring and low risk of fatality if one is struck by motorized vehicle), while focusing on areas where many fatal accidents occur might result in great positive effects. This approach might be usable for types of locations (e.g. an urban environment with a certain composition of exposure) or traffic environments (e.g. some given traffic environment or speed limit) where several fatal accidents occur; however, it might also render speed policy changes reactive instead of proactive.

Consider how those fatality risk curves can be applied from a system perspective and what knowledge can be gained from them. The curve from Rosén and Sander (2009) gives the fatality risk values of 57%, 35%, 3.6% and 1.5% for impact speeds of 80, 70, 40, and 30 km/h, respectively. From an individual road user's perspective, a change from 80 to 70 km/h is perceived as more important than a change from 40 to 30 km/h. But from the system perspective the opposite is true. If there are 100 fatal (and several non-fatal accidents) which occur at 80 km/h, then had the speed been 70 km/h (relative risk ratio of 0.61) 39 of those survived. If there are 100 fatal (and several non-fatal accidents) which occurs at 40 km/h, then had the speed been 30 km/h (relative risk ratio of 0.42) 58 of those survived. This is, of course, a simplified example; however, it demonstrates that from a system perspective, the relative risk is of greater importance.

To describe this relation, *paper II* created a relative risk model, the relative fatality risk curve, based on two absolute fatality risk curves (Rosén and Sander, 2009, Tefft, 2011). Figure 32 shows how the relative fatality risk ratio changes as the impact speed is changed from a base speed. This might, with some simplifications, be read so that reducing the speed by 10 km/h from the common urban speeds of 30, 40 and 50, km/h would reduce the number of fatalities for struck pedestrians by roughly half. In addition, increasing the speed by 10 km/h might result in an increased number of fatalities for struck pedestrians somewhere between 50% and 100% (this estimation

does not consider that speed is also related to the risk of an accident occurring in the first splace, further, impact and travel speeds might differ from the speed limit).

The earlier fatality risk curves were often used to define some 'safe' speed, at which there would be a low probability of fatality or limited benefits of lowering the speed any further. The relative fatality risk curve demonstrates that this is a somewhat flawed approach. The system perspective shows that it is not possible, given current knowledge, to define some speed at which there are no benefits from further lowering the speed. On the contrary, at least in theory, (impact) speed reductions from 30

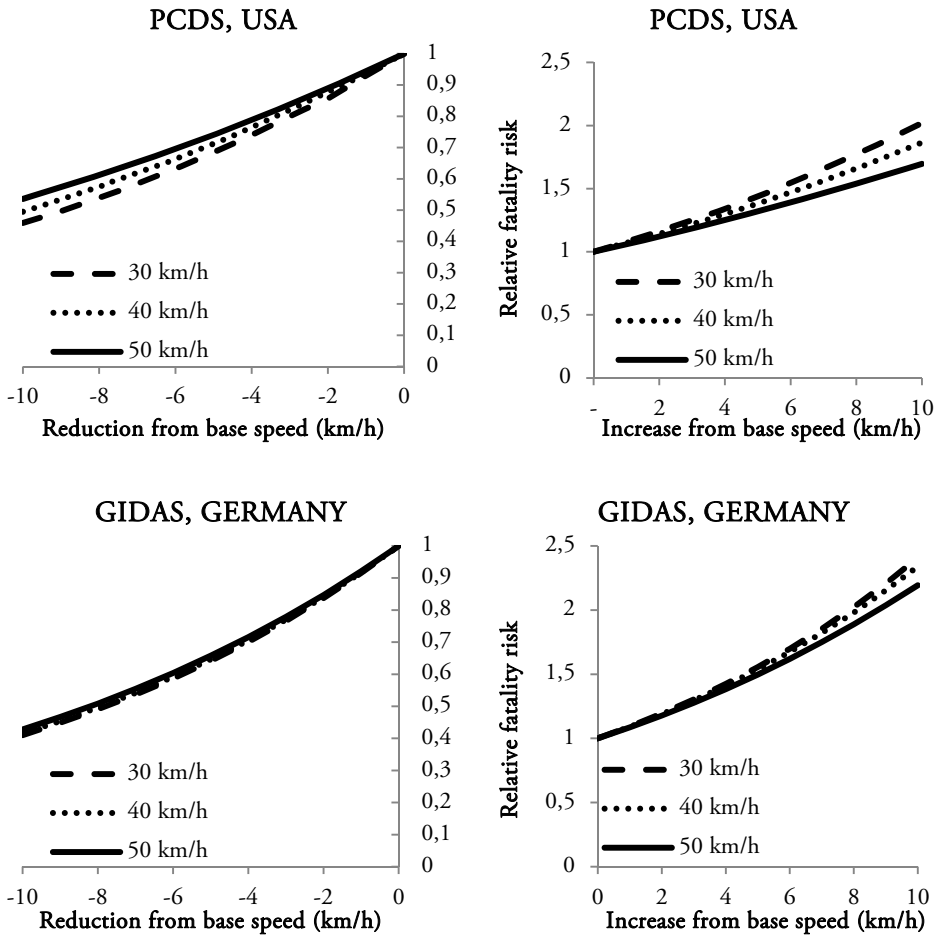

Figure 32: Relative fatality risk curves by base speeds, based on fatality risk curves on impact speed from Rosén and Sander (2009) (GIDAS, Germany) and Tefft (2011) (PCDS, USA) (*paper II*).

km/h have an an similar proportional effect to that of speed reductions from 50 km/h. That there is no safe speed[12] is not surprising, but a simple fall accident can result in serious injuries (Öberg, 2011). In fact, the results show that, contrary to the visual perception of the absolute fatality risk curves, that the relative risk reduction is similar regardless of what the initial speed was (i.e. no matter whether the speed was reduced from 50, 40 or 30 km/h). Therefore, from the number of accidents perspective, those results might suggest that when applying changes in speed policy to reduce the number of accidents, the focus should not be on where the absolute risk of fatality is highest, but rather on where the probability of fatal accidents occurring is high, but that, of course, relates to both the risk of an accident occurring and the consequences of that accident.

This approach, i.e. the relative approach, has some limitations. (1) It is not possible to accurately determine the absolute fatality risk and the form of that curve might not be a perfect S curve; therefore, there is some uncertainity regarding the shape of the relative risk curve. (2) The risk of fatality depends on many factors other than speed, such as age and vehicle type; hence, the optimal situation would be to have an absolute and relative fatality risk curve based on Swedish data that would be more valid for use in Sweden (even though the relative nature of the approach reduces those effects). (3) Because of underreporting and in order to maintain the causal relation, the deviation from the base speed should not be too great. (4) Since the fatality risk curves are mainly based on accidents at urban speed levels, the relative fatality curve should not be used for speeds higher than that. (5) Measurement error (i.e. determination of the impact speed) can have substantial influence on the relative fatality risk curve. (6) The absolute and relative fatality risk curves do not consider the other two dimensions, risk and exposure, which can considerably influence the number of accidents and hence the number of serious and fatal injuries. (7) The population is constantly changing; so the fatality risk against impact speed will change as well. However, testing the curve´s robustness (*paper II*) shows that the relative fatality risk should remain fairly robust even though the absolute fatality risk changes with different compositions of the population. (8) The relative fatality risk curve is a model aimed at better understanding what knowledge can be found in the absolute fatality risk curves and what they say about the importance of speed and speed changes. It is, however, like all mathematical models, not entirely accurate and should be considered more as a guiding model (as should the absolute fatality risk curves).

[12] It is difficult to define the concept *safe speed*. The most general definition is a speed at which no accident will occur. In that case, the only safe speed can be 0 km/h; thus, this is an impractical definition that yields nothing. A more practical approach is to define safe speed as a speed at which the probability of an accident that results in serious or fatal injuries is very low, and a speed that, if reduced, yields no significant traffic safety benefits.

5.1.3 Concluding remarks

The impact speed is of great importance for the probability of survival and the number of fatal accidents. From the available models, however, it is not possible to determine some safe speed; one can say only that the fatality risk increases with higher speed and decreases with lower speed. Even though the absolute fatality risk in earlier studies was underestimated, that should not influence speed policy, since this work suggests that when applying fatality risk values for speed policy changes, more focus should be on relative fatality risk values than on absolute fatality risk values. The goal should not be some 'acceptable' fatality risk, but rather to reduce the loss of health through traffic accidents. Finally, even though the mathematical models do not provide fully accurate descriptions of reality, applying a relative approach provides a good idea of how important changes in impact speed are for the chance of survival and a guide for future changes in speed policies.

5.2 The relation between speed environment and injury severity/outcome for struck pedestrians and bicyclists

The relation between the speed environment and the injury severity/outcome for pedestrians and bicyclists struck by motorized vehicles was investigated in *papers III* and *IV*.

5.2.1 Main results

The travel speed was measured at accident locations where pedestrians and bicyclists had been injured. The cumulative distributions of mean travel speeds at the accident locations (by injury severity/outcome) are presented in figures 33 and 34. Both for struck pedestrians and bicyclists, minor injury and serious injury accidents occurred in similar speed environments. Further analysis of the data, however, shows that even though the accidents occured in locations with similar mean travel speeds ($p=0.114$ for struck pedestrians, $p=0.276$ for struck bicyclists), the mean age of the victims was much higher among those who were seriously injured than among those who suffered minor injuries ($p=0.030$ for struck pedestrians, $p=0.003$ for struck bicyclists), see table 6.

One of the most striking results is that several accidents resulting in serious injuries for both struck pedestrians and struck bicyclists occurred at sites where the mean travel speed was below 30 km/h. It is possible that this was because the vehicle involved in the accident was driving above the mean travel speed, however *this might also indicate that 30 km/h is not as safe as often assumed*, at least not if the aim is to

prevent serious injuries. It is also interesting that greater part of accidents involving bicyclists who suffered serious injuries occurred in low speed environments than for pedestrians. As discussed in *paper IV*, there are several differences between pedestrians and bicyclists involved in collisions with motorized vehicles, but most of those differences favor the bicyclists, i.e. bicyclists generally have a lower probability of sustaining serious or fatal injuries than pedestrians (Maki et al., 2003, Otte et al., 2012). One possible hypothesis is that where the speed of the motorized traffic is low, the speed of the bicyclists themselves becomes more important, as bicyclists can travel at up to 40 km/h or more (even though bicycling is frequently at lower speeds, Thompson et al., 1997).

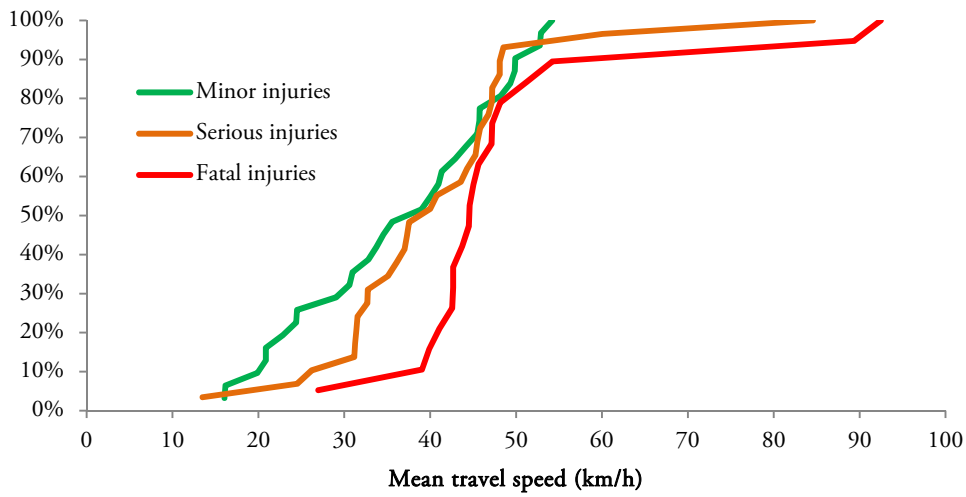

Figure 33: The cumulative distribution of mean speeds at accidents sites for pedestrians struck by motorized vehicle (*paper III*).

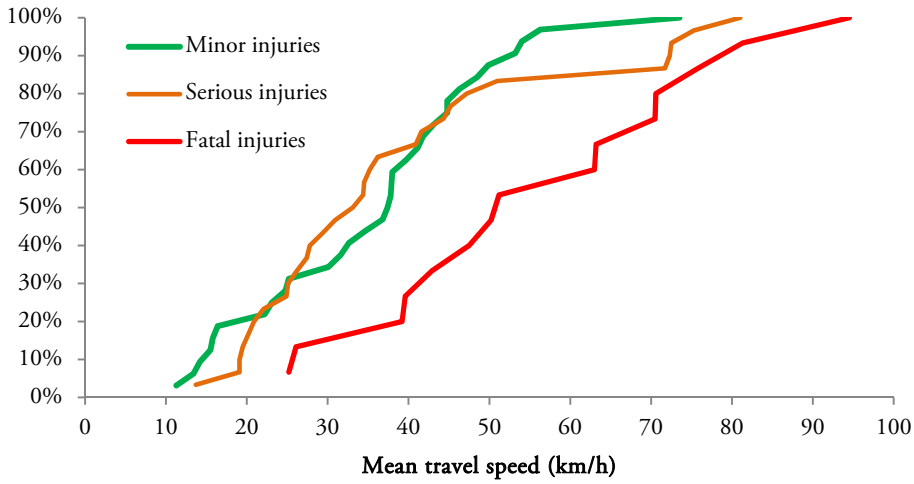

Figure 34: The cumulative distribution of mean speeds at accidents sites for bicyclists struck by motorized vehicle (*paper IV*).

Table 6: Mean travel speed at accident sites, mean age and injury severity/outcome for struck pedestrians and bicyclists (standard deviation within paranthesis).

	Pedestrians		Bicyclists	
	Mean travel speed (km/h)	Mean age (years)	Mean travel speed (km/h)	Mean age (years)
Minor injuries	36.6 (11.7)	41.4 (26.5)	35.5 (14.6)	36.9 (19.1)
Serious injuries	40.5 (12.6)	55.5 (30.2)	38.1 (19.0)	52.3 (22.8)
Fatal injuries	48.9 (15.8)	65.2 (24.7)	56.1 (20.2)	61.7 (13.4)

The fatal accidents show a very clear pattern, though the pattern differs for struck pedestrians and bicyclists. Most (63.2%) of the fatal pedestrian accidents occur in a speed environment where the mean travel speed is between 40 and 50 km/h, probably owing to the combination of exposure (the probability of interaction is low in other speed environments) and the low risk of an accident occurring where the speed is lower. This makes the 40 to 50 km/h environment a tempting target for speed reductions; because, according to the number of accidents perspective, it is there that one can influence most of the fatal pedestrian accidents (but this effect might arise partly because great part of the urban road network belongs to this speed environment). Fatal accidents for struck bicyclists are not as concentrated in terms of speed environment. In fact, those accidents are almost linearly distributed over the speed spectrum from 25 to 90 km/h. That so great proportion of those accidents

occurs in high speed environments (rural environments) makes it more challenging to reduce fatal accidents for bicyclists through speed policy or speed measures.

To extend the analysis, all accidents within datasets 1 (i.e. all accidents involving pedestrians and bicyclists of known age who were struck by motorized vehicles and injured in Sweden between 2004 and 2008) that included speed limit at the accident site were analyzed, and the injury severity/outcome was compared to the speed limits (see table 7). This analysis shows that the proportion of serious and/or fatal injuries increases with higher speed limits. Furthermore, those results support the other findings, that a great proportion of struck pedestrians and bicyclists suffer serious injuries in 30 km/h speed environments. The proportion of serious injuries that occur in those low speed environments is only slightly greater for struck bicyclists than for pedestrians (8.4% for bicyclists compared to 7.4% for pedestrians).

Table 7: The distribution of injury severity/outcome by speed limits.

Speed limit	Pedestrians				Bicyclists			
	Minor	Serious	Fatal	All	Minor	Serious	Fatal	All
Unknown	3 864	621	81	4 566	4 675	475	38	5 188
	84.6%	13.6%	1.8%	100%	90.1%	9.2%	0.7%	100%
20-30 km/h	335	59	11	405	302	49	2	353
	82.7%	14.6%	2.7%	100%	85.6%	13.9%	0.6%	100%
40-50 km/h	2 080	605	86	2 771	3 086	431	41	3 558
	75.1%	21.8%	3.1%	100%	86.7%	12.1%	1.2%	100%
60-70 km/h	140	85	30	255	127	74	15	216
	54.9%	33.3%	11.8%	100%	58.8%	34.3%	6.9%	100%
80+ km/h	55	50	64	169	41	29	11	81
	32.5%	29.6%	37.9%	100%	50.6%	35.8%	13.6%	100%

Figures 35 and 36 show each accident plotted by victim´s age and speed environment. Those figures reinforce the previous analysis results with regard to age and speed environment, they also demonstrate that the age has a clear influence; the fatal accidents are concentrated among seniors.

Overall, it seems from the data that serious injury accidents are rare in traffic environments where the mean travel speed is below 20 km/h and that fatal accidents are rare in traffic environments where the mean travel speed is below 40 km/h. Observe, however, that this study excludes accidents in which the vehicle travels over the victim, i.e. run over accidents; which are often serious or fatal and sometimes occur at low speeds.

To deepen the analysis, multinomial logit models were created, one for struck pedestrians and one for struck bicyclists. The parameters of the models and odds ratios are shown in table 8 (page 85), where odds ratios represent how the probability of the given injury severity/outcome changes with the independent variable. For the most part, mean travel speed and age were statistically significant, but in some cases they were not. (1) The age was not statistically significant for serious injuries compared to fatal injuries ($p=0.12$ for pedestrians and $p=0.18$ for bicyclists). This was unexpected; however, combining serious and fatal injuries resulted in highly statistically significant parameters for age ($p=0.005$ for pedestrians and $p=0.001$ for bicyclists). (2) The speed variable between minor and serious injuries was not statistically significant ($p=0.144$ for pedestrians and $p=0.451$ for bicyclists, this was tested seperatelly by creating multinomial logit models where the reference group was minor injuries). This was less surprising because the preliminary analysis of the speed distributions for minor and serious injury accidents showed no greater differences. There are at least three possible explanations for the limited differences in the speed

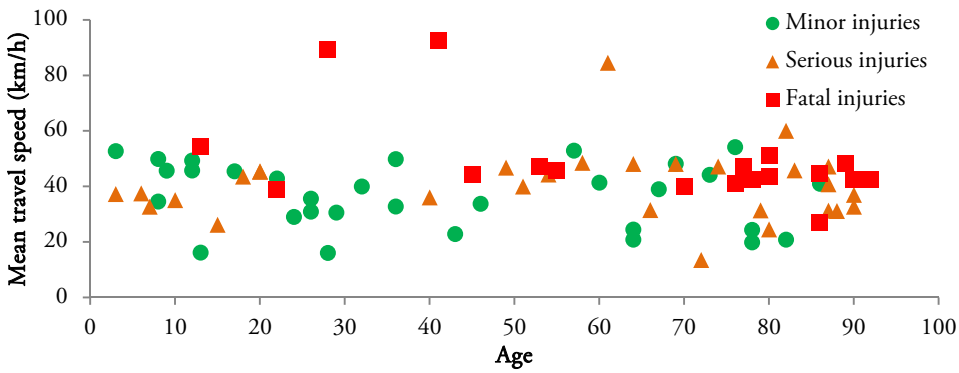

Figure 35: Accidents between pedestrians and motorized vehicles by injury severity/outcome, age, and speed environment (*paper III*).

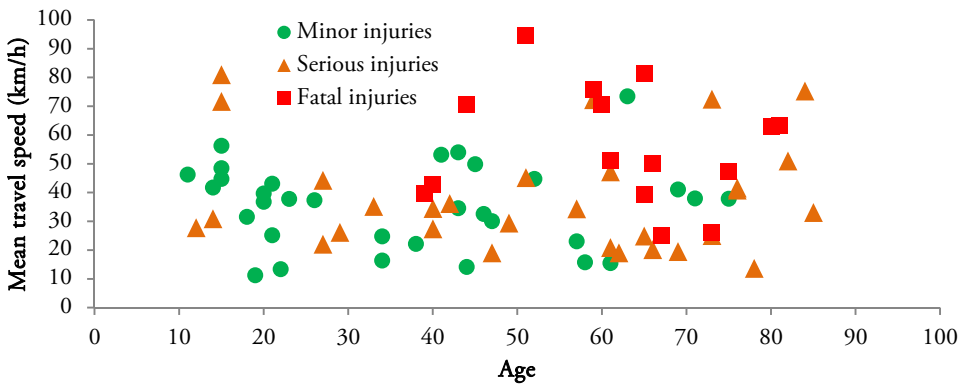

Figure 36: Accidents between bicyclists and motorized vehicles by injury severity/outcome, age, and speed environment (*Paper IV*).

distributions. (a) This study excluded locations with very low traffic volumes, many of which were low speed environments; (b) the underreporting of minor injuries is far greater than the underreporting of serious injuries (Jonsson et al., 2011). Both those factors could reduce the differences between the speed distributions for those two injury severity groups, resulting in a lack of statistical significance for the speed variable. (c) Finally, the speed of the individual car involved in an accident, might systematically differ from the mean travel speed, that is, cars that are involved in minor injury accidents might have been in a greater degree driving below the mean travel speed, while those involved in serious injury accidents might have been driving above the mean travel speed. Since it is not possible to determine the travel speed of the vehicles involved in the accidents, this cannot be studied here; however, Richards et al. (2010) showed that the proportion of accidents involving excess speed as a contributory factor to increase with injury severity, supporting this hypothesis.

From those models, an absolute injury severity/outcome risk curve can be created (but refer to *paper II* for the limitations of this type of risk curve; the same limitations apply as for a fatality risk curve based on impact speed). Figure 37 shows a fatality risk curve estimated from the multinomial logit models, based on mean travel speed for a 40 year old pedestrian and a 40 year old bicyclist struck by a motorized vehicle (the model for the pedestrian was for all vehicle types, while the vehicle type for the bicyclist was 'passenger vehicle or unknown'). The fatality risk curves for mean travel speed show higher speeds than the fatality risk curves based on impact speeds (Rosén, 2013, Rosén and Sander, 2009). That the fatality risk is so low makes it even more difficult to use the individual perspective on fatality risk curves based on mean travel speed, compared to fatality risk curves based on impact speed. Figure 38 shows the risk of serious injuries compared to mean travel speed for same case as before; the risk of serious injuries seems to be lower at lower mean travel speeds; however, pedestrians seem to be more heavily influenced by mean travel speed at urban speed levels. Observe, that the risk of serious injuries will theoretically, both for impact speed (Davis, 2001) and for mean travel speed (figure 38), decrease again at high speeds, because at some point all who suffer serious injuries will die from those injuries, in other words, the risk of fatality will rise faster with higher speeds than the risk of serious injuries will.

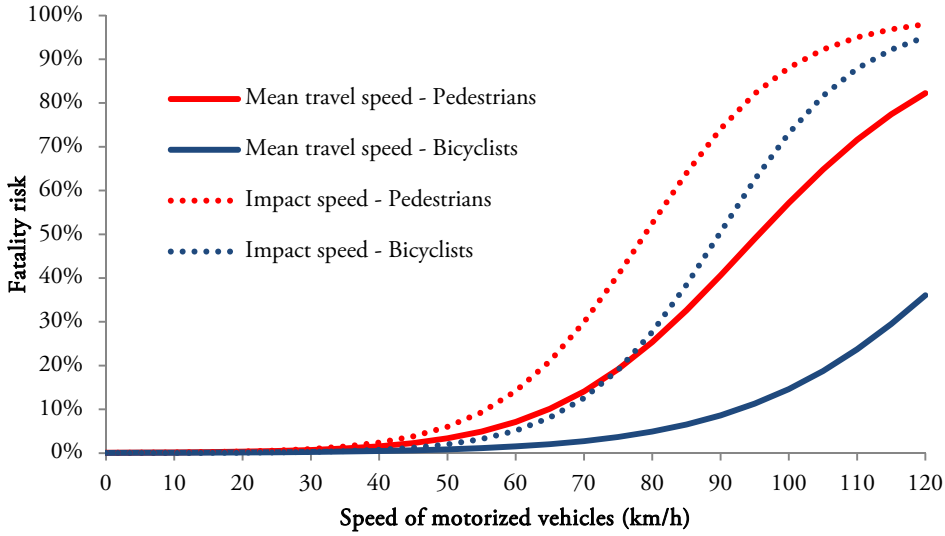

Figure 37: Estimated fatality risk for a 40 year old struck pedestrian and a 40 year old bicyclist, according to the multinomial logit models, comparing fatality risk against impact speed for struck pedestrians (Rosén and Sander, 2009) and struck bicyclists (Rosén, 2013). The model for struck bicyclists against impact speed does not consider the victim´s age or the vehicle type.

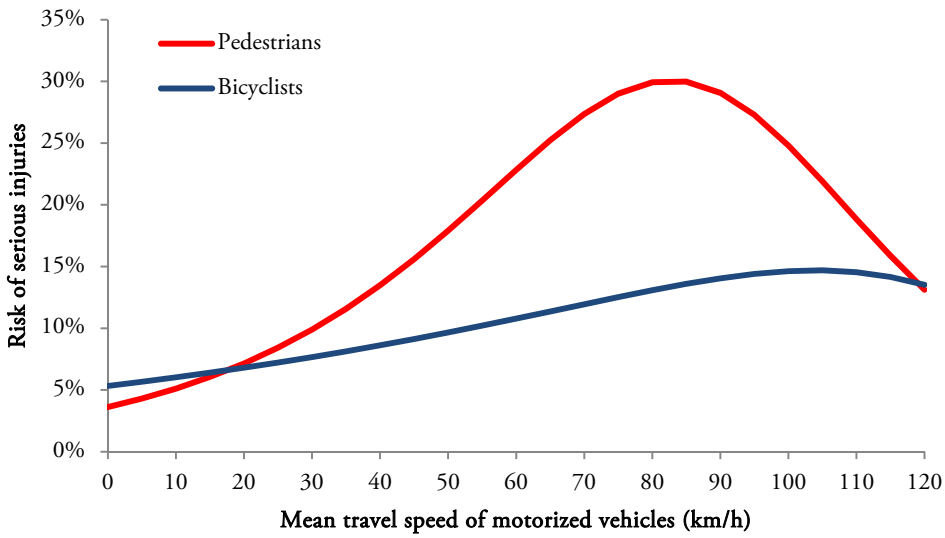

Figure 38: Risk of serious injuries against travel speed for a 40 year old pedestrian and a 40 year old bicyclist according to the multinomial logit models.

Table 8: Parameters for the Multinomial Logit models for struck pedestrians and bicyclists (vehicle type was not included in the pedestrian model).

Injury severity		Pedestrians			Bicyclists		
		Estimate	Odds ratios	P value	Estimate	Odds ratios	P value
Minor injuries	Interceptor	9.006			10.097		
	Speed	-0.086	0.92	0.004	-0.062	0.94	0.004
	Age	-0.039	0.96	0.004	-0.063	0.94	0.003
	Heavy vehicle				-1.974	0.14	0.142
Serious injuries	Interceptor	4.965			5.788		
	Speed	-0.050	0.95	0.042	-0.049	0.95	0.009
	Age	-0.020	0.98	0.12	-0.026	0.97	0.182
	Heavy vehicle				-1.511	0.22	0.160

5.2.2 Validation

It is interesting to investigate how well the injury risk models based on dataset 2 (presented in table 8 and figures 37 and 38) fit the general accident statistics. This can be done indirectly by comparing those models to the risk of serious and/or fatal injuries against speed limits from datasets 1 (i.e. all injury accidents that occurred in Sweden 2004-2008 for which the victim´s age and the speed limit are known). Since the injury severity/outcome in accidents with a registered speed limit is biased compared to all accidents in datasets 1 (i.e. the accidents with registered speed limits had a higher proportion of serious and/or fatal injuries than did all registered accidents), the proportions were scaled to make them representative for the whole dataset 1. The multinomial logit models were applied to all the victims on an individual level, and it was assumed that the mean travel speed in each case was equal to the speed limit. Then the overall probability of serious and/or fatal injuries, according to the multinomial logit models, was compared to the scaled injury risk from datasets 1 (where the speed limit was known); see figures 39 to 44.

There are some noteworthy differences between the values predicted in the models and the values observed in datasets 1. (a) The models seem to overestimate the fatality risk for pedestrians struck when the speed limit is 50 km/h. The mean travel speed at accident locations with a speed limit of 50 km/h often differs from the speed limit. This means that the model may be using a mean travel speed that is too high or too low; if the mean travel speed had been measured, this might have influenced the fatality risk predicted in the models. (b) In addition, some discrepancies appear at

higher speeds. This further supports the statements made in *paper II*, that because the models are mainly based on accidents that occurred in urban settings (and at urban speed limits), the model should not be applied to high speed environments. Finally, (c) it is striking that the observed fatality risks at the speed limit 100/120 km/h is so low for both pedestrians and bicyclists. However, relatively few cases occurred at this speed environment in datasets 1, only 45 pedestrians (40% of the fatally injured, the reason this value differ from those presented in figure 41 is that those values were scaled to be representative of the whole dataset 1) and 7 bicyclists (14% of them fatally injured). In addition, it is possible that in cases where a pedestrian or bicyclist was struck on a motorway, some special situation arose so that the real mean travel speed at the time of the accident was much lower than the speed limit or the normal mean travel speed, or that the scaling process is not representable for the accidents in high speed environments (perhaps the underreporting is lower in high speed environments compared to other speed environments).

Overall, the model fits the data relatively well, given all the limitations of this validation method; however, caution is in order if the models are to be used for higher speeds.

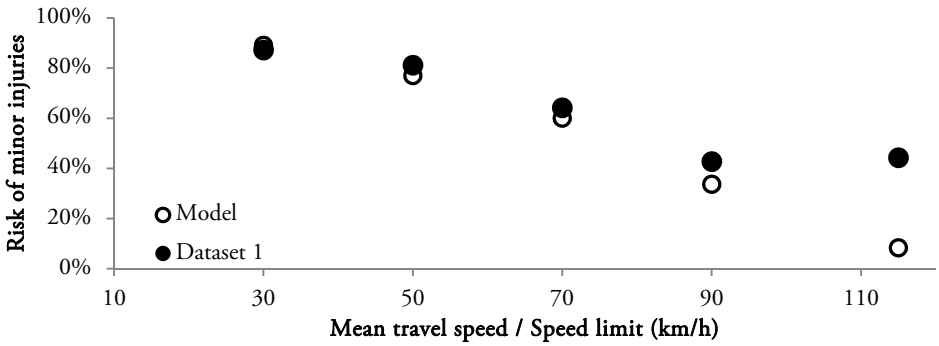

Figure 39: Comparison of the risk of minor injuries for struck pedestrians between the multinomial logit model and dataset 1 (115 km/h is the combination of the speed limits 110 and 120 km/h).

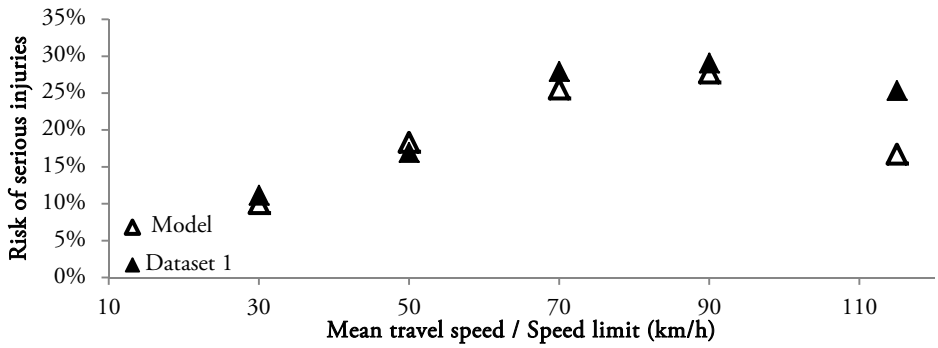

Figure 40: Comparison of the risk of serious injuries for struck pedestrians between the multinomial logit model and dataset 1 (115 km/h is the combination of the speed limits 110 and 120 km/h).

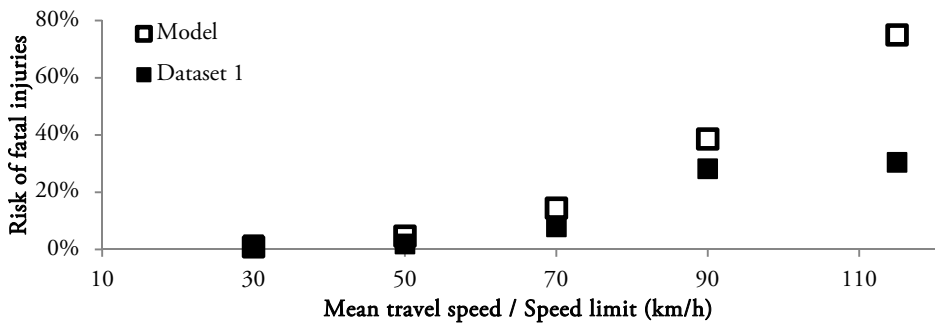

Figure 41: Comparison of the risk of fatal injuries for struck pedestrians between the multinomial logit model and dataset 1 (115 km/h is the combination of the speed limits 110 and 120 km/h).

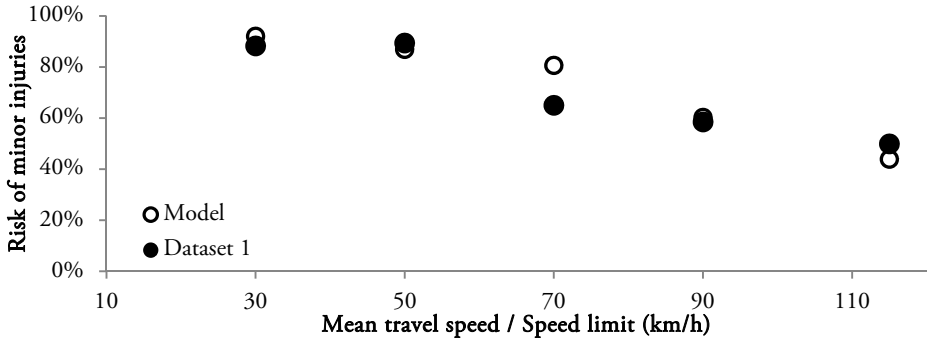

Figure 42: Comparison of the risk of minor injuries for struck bicyclists between the multinomial logit model and dataset 1 (115 km/h is the combination of the speed limits 110 and 120 km/h).

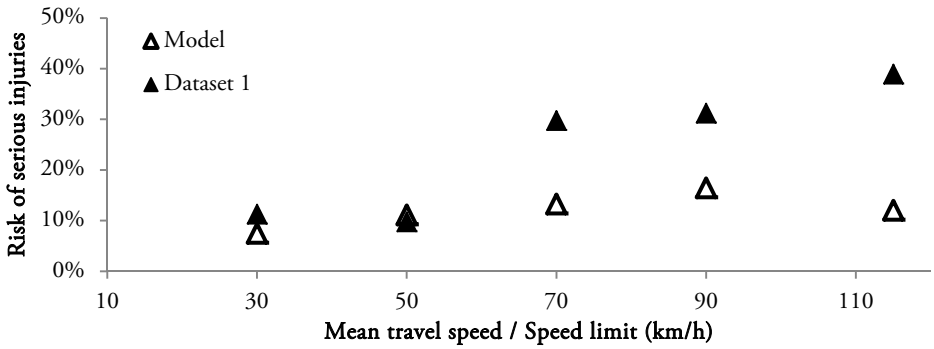

Figure 43: Comparison of the risk of serious injuries for struck bicyclists between the multinomial logit model and dataset 1 (115 km/h is the combination of the speed limits 110 and 120 km/h).

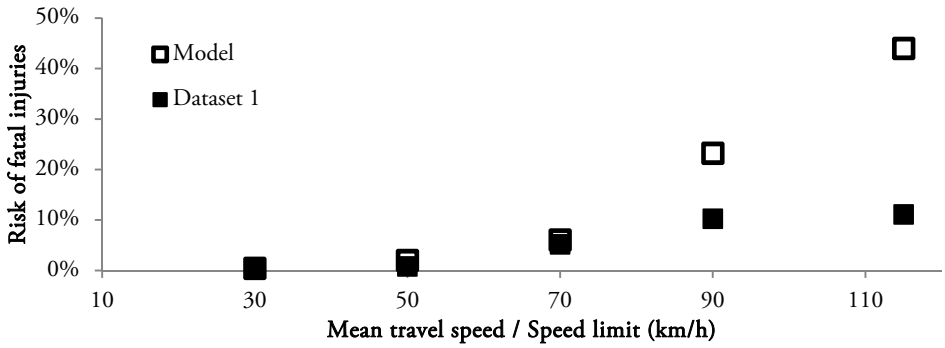

Figure 44: Comparison of the risk of fatal injuries for struck bicyclists between the multinomial logit model and dataset 1 (115 km/h is the combination of the speed limits 110 and 120 km/h).

5.2.3 Comparison to the power model

The power model has been frequently used to describe how the relative number of accidents (and sometimes the number of road users) of different injury severity/outcome is influenced by the mean mean travel speed (Elvik, 2014b, Nilsson, 2004). The Power model applies relative approach and describes how the number of accidents of different injury severity/outcome can be expected to change with changes in mean travel speed. The base model is demonstrated in equation 12, where N_{before} and N_{after} are the number of accidents, of some given injury severity, before and after some change in mean travel speed, v_{before} and v_{after} is the mean travel speed for the before and after scenario and β is a constant that differs depending on the injury severity of the accidents.

Equation 12: $$\frac{N_{after}}{N_{before}} = \left(\frac{v_{after}}{v_{before}}\right)^{\beta}$$

Harkey et al. (2008)[13] critizises the Power model, because the model is not dependent on the inital speed (only relative speed), and that a change in speed from 10 km/h to 8 km/h would result in similar change in number of accidents as change from 100 km/h to 80 km/h. They therefore suggested two alternative approach, the exponent models, see equations 13 and 14, where α_1 is constant depending on the injury severity, α_2 is a constant meant to describe a speed for safe maneuvering based on design; and γ and φ are constants, both models try to incorporate the influence of the initial speed, not only relative speed.

Equation 13: $$\frac{N_{after}}{N_{before}} = e^{\alpha_1 \ln\left(\frac{v_{after}}{v_{before}}\right) - \alpha_2\left(\frac{1}{v_{after}} - \frac{1}{v_{before}}\right)}$$

Equation 14: $$\frac{N_{after}}{N_{before}} = e^{\gamma\left(v_{before} - v_{after} + \frac{\varphi}{2}\left({v_{before}}^2 - {v_{after}}^2\right)\right)}$$

Elvik (2013b) reasoned that the exponent models had four drawbacks, it excluded residential roads, it did not succeed for property damage only accidents, it relied on

[13] The report from Harkey et al., 2008, included an appendix whit a paper that is written by Hauer, E., Bonneson, J., 2006. An empirical examination of the relationship between speed and road accidents based on data by Elvik, Christensen and Amundsen. To my knowledge, this paper was not published seperatelly.

individual data points, with varying quality and the model was complex. Elvik (2013b, 2014b) investigated the possibility of creating a more parsimonious version, see equation 15, where α and β are constants. Elvik (2013b) showed that it varied depending on injury severity/outcome which model, power model or exponent model, performed better, but both models performed well. The relative number of accidents, i.e. how great influence a speed change will have on the number of accidents can then be calculated from equation 16. This reveals some interesting properties of the model, as were pointed out by Nielsen and Andersen (2014) namely that the relative change in number of accidents is, according to this version of the exponent model, only dependent on the absolute change in speed, not the initial speed. It therefore seems that we have exchanged one problem (or simplification) for another. The power model does not consider the intial speed level, only the relative changes in speed; and Elvik´s exponent models only considers the absolute change in speed, neglecting the intial speed level before and the relative change in speed.

Equation 15: $$Relative\ number\ of\ Accidents = \alpha e^{\beta v}$$

Equation 16: $$\frac{N_{after}}{N_{before}} = \alpha e^{\beta(v_{after} - v_{before})}$$

Anyhow, it is worth comparing these models to the multinomial logit models discussed in this thesis. Since there are three alternative exponent models (one from Elvik, 2014b, and two from Harkey et al., 2008), and Elvik (2013b) showed that the performance of Elvik´s exponent model and the power model was similar, it was decided to only compare the multinomial logit models to the power model.

The power model is focused on the number of accidents (combining the risk and consequence dimension) and the relative change thereof, while my models are focused on the injury severity/outcome. To render the models comparable the power model has to be rewritten to show how the probability of injury severity/outcome *i* changes with changes in mean travel speed, see equation 17, where RR_i is the relative risk of injury severity *i* for some hypothetical speed change.

Equation 17: $$RR_i = \left[\frac{N_{i\ after}}{N_{all\ injuries\ after}}\right] \Big/ \left[\frac{N_{i\ before}}{N_{all\ injuries\ before}}\right]$$

The exponents of the power model has been estimated in several studies, and shown to vary depending on among other traffic environment (Elvik, 2009b) and speed environment (Elvik, 2013b). Since my models are based on both rural and urban accidents I decided on using the exponents from Elvik (2009b), i.e. 2.0 for number of injuries, 3.0 for serious injuries and 4.3 for fatalities. It should however be noted that

those parameters are based on all accident types (not only pedestrians and/or bicyclists) and are therefore not fully compatable.

Finally, the models from this thesis must be adjusted to be relative risk curves, see equation 18, where R_i is the risk of injury severity/outcome *i*. Since my models include the victim´s age as a variable and are divided by road user group (pedestrians or bicyclists) two relative risk curves were created for each road user group: 20 years old and 65 years old. Comparison between the models is shown in figures 45 and 46.

Equation 18: $$RR_i = \frac{R_{i\ after}}{R_{i\ before}}$$

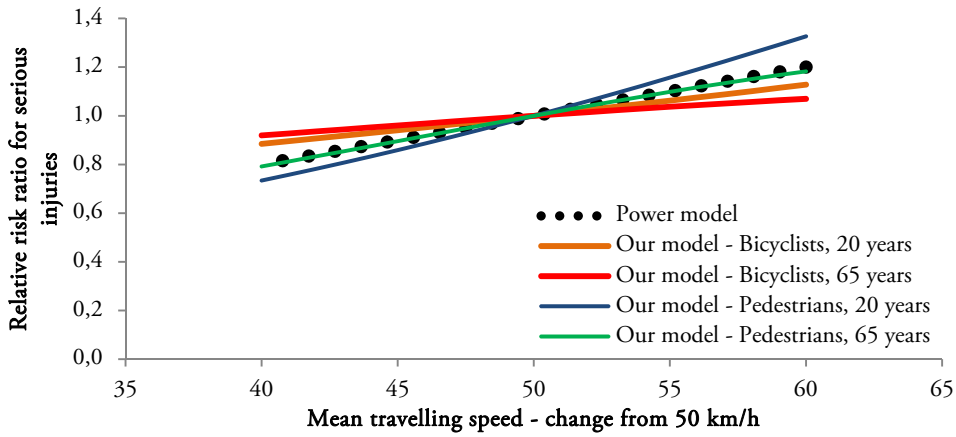

Figure 45: Comparison of how changes in mean travel speed influence the risk of serious injuries for all accidents (power model), struck pedestrians and struck bicyclists according to our models (*papers III* and *IV*), aged 20 and 65.

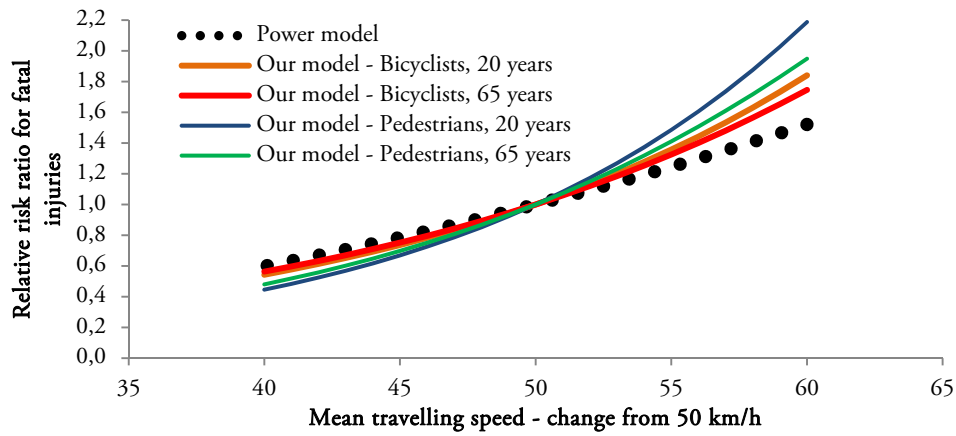

Figure 46: Comparison of how changes in mean travel speed influence the risk of fatal injuries for all accidents (power model), struck pedestrians and struck bicyclists according to our models (*papers III* and *IV*), aged 20 and 65.

My models shows higher relative risk ratios for serious injuries for young pedestrians than the power model does, while the ratios are slightly lower for bicyclists. For fatal injuries, our models show higher relative risk ratios for both pedestrians and bicyclists than the power model does. This suggests that the risk of serious and fatal injuries is in most cases, according to our models, more sensitive to changes in mean travel speed compared to the power model.

There are some fundamental differences between the models proposed here and the power model. The most important being that the power models is based on all accidents, while our models are specific to pedestrians and bicyclists, but since pedestrians and bicyclists are generally more fragile, it is not unexpected that these accidents show greater sensitivity to changes in mean travel speed than all accidents types combined do (where most accidents involved only cars). Therefore, the models seem to support each other. It should however also be noted that to better understand those relations, might require including among others the speed distribution and proportion of drivers travelling at extreme speeds (Taylor et al., 2000).

5.2.4 Discussion

Now, let us consider what these results mean for speed policy and our understanding of the influence of speed on traffic safety. First of all, when applying the number of accidents perspective, the data seem to indicate that serious injuries are rare when the mean travel speed is below 20 km/h and that fatal injuries are rare when the speed is below 40 km/h. This result is interesting, if these speeds might indicate some thresholds for what the human body can endure. However, the amount of data in our study is too small to make such a determination; hence, further studies are required. Furthermore, a great proportion of the fatal pedestrian accidents can be influenced by reducing the travel speed in 50 km/h environments, supporting a speed limit (and speed reducing measures) of 40 km/h where there is interaction between pedestrians and motorized vehicles. Even so, it is not sufficient to focus on 50 km/h environments in order to reduce the number of serious injury accidents, for that the speed must be reduced further. The multinomial logit models also show that the probability of serious injuries increases relatively fast with higher mean travel speed (see figure 38).

The relative approach provides additional insights. The relative fatality risks for the mean travel speed suggests that there might be potential in decreasing the travel speed to reduce fatal accidents, where the relative risk ratios for fatality risk results in roughly halving the fatality risk with every speed reduction of 10 km/h; and yielding a relative risk ratio of 0.7-0.75 (pedestrians) and 0.9 (bicyclists) for serious injuries at urban speeds. For comparison, the relative risk ratios for fatal injuries in accidents in dataset 1 (where the speed limit was registered) that occurred at the speed limits 50 and 30 km/h are 0.88 (pedestrians) and 0.49 (bicyclists); those for serious injuries are

0.67 (pedestrians) and 1.15 (bicyclists). Those results differ somewhat, however, the relative risk values from the speed limit proxy show similar directional influence to that of the theoretical model (with one exception); but there are several complicating factors that influence comparison between speed limit and travel speed. Also, a theoretical model such as the relative injury risk curve should be considered an aiding model rather than a precise tool, especially when it is based on mean travel speed that has ´only´ probabilistic relation with impact speed (and hence with the injury severity/outcome).

The general conclusion is that lower mean travel speed is likely to result in a reduced number of fatal accidents, possibly even in a reduced number of serious injuries (observe, though that reduced speed can in theory result in an increased probability of serious injuries, because the risk of fatality decreases faster than the risk of serious injuries does, see figure 38). These results also align with the power model.

Those assumptions are, however, dependent on the assumption that there is a causal effect between mean travel speed and the injury severity/outcome, when in fact the relation is probabilistic. But can one assume that the mean travel speed has a causal relation with the injury severity/outcome? Elvik and Vaa (2004) discuss nine guiding criteria for determining whether the effect (of a treatment) is causal rather than only correlative; in this case, those can be summarized into seven critieras: (1) there must be a strong statistical association, where stronger statistical relationship gives more support to the relation being causal than a weak relationship; (2) any subset within the data should show consistent relationship; (3) it must be clear what is cause and what is consequence; (4) the effect should remain when controlling for important confounding factors; (5) The relation should show a dose response pattern, i.e. higher speed ´dose´ should result in higher injury severity/outcome; (6) the reason for the causal relation (the underlying mechanism) should be known; and (7) the theory and evidence from other studies should support the findings. The results presented here fullfill, at least partly, criterias 1, 3, 4, 5 and 6, even though it would be preferable to increase the dataset to estimate in greater detail the size of the effect and with more detailed data it would be possible to test for more confounding factors (and to investigate if a higher statistical significance level can be achieved). The second crition was not tested due to small dataset, however, we can, with some limitations, view that we have two sub sample where we are investigating the relation between mean travel speed and injury severity/outcome, namely, pedestrians and bicyclists. The last critierion is partly fulfilled, but this fits the theory given that there is a probabilistic relation. Also, studies that estimated the power model for different injury severities/outcomes seems to support our findings. However, since this is a cross sectional study, and the first study (to our knowledge) to apply this methodology on this relation in this manner, it is not possible to compare the results to similar studies. Overall, our conclusion is though that the mean travel speed has a probabilistic relation to the travel speed of the vehicle involved in an accident, but it is likely that the travel speed of the vehicle has a causal relation with the injury severity/outcome.

The results show that there is a considerable difference in injury severity/outcomes for struck pedestrians versus struck bicyclists, where pedestrians are at greater risk of suffering serious or fatal injuries compared to bicyclists (exception is that according to the models the bicyclists are more likely to suffer serious injuries when the speed is below 15 km/h, however, since only handful of accidents occurred in that speed environment, no conclusion can be drawn if this is in fact a real effect or simply a statistical artifact.

This is in agreement with prior studies based on impact speed who have shown pedestrians to have higher fatality risk than bicyclists (Rosén, 2013). It is also not unexpected that the injury severity/outcome would differ between those two groups since there is considerable difference in the accident mechanics. Maki et al. (2000) showed that the head impact velocity and impact angle are different for bicyclists and pedestrians, Ito et al. (2014) showed bicyclists to rotate in collisions (in simulations). Watson (2010) showed through simulations that, depending on vehicle speed and vehicle type, there was sometimes a sliding phase which the victim moved up the vehicle´s bonnet influencing the location of the head´s impact on the vehicle, this was more common for bicyclists than for pedestrians. Watson (2010) even showed that it might matter whetеher the bicycle´s pedal (the victim´s foot) was up or down at the moment of impact and that, among other thing, the head impact location differed from that of pedestrians.

5.2.5 Limitations

There are some limitations to these results and the models presented here.

(1) Most of the data are based on accidents that occurred in urban settings. Therefore, any model built from these data should be considered valid primarily for urban speed environments.

(2) The injury risk models are influenced by underreporting, and further, the underreporting degree might vary for different speed environments; this diffference would influence the relative risk ratios.

(3) The injury risk models do not take into consideration the influence on the risk (risk of an accident occurring) and exposure dimensions.

(4) The study is based on accident reports and is therefore sensitive to the accuracy of those reports; for this reason accident reports whose quality was deemed low were excluded.

(6) Swedish hospitals changed the injury classification from AIS1990 to AIS2005 on the 1st of January 2007.

(7) There might have been unidentified changes in the physical layout of the accident site or in road user behavior between the time of the accident and the time of the speed measurement.

(8) Locations with low traffic flows were excluded from the study.

(9) The models are based on relatively few accidents, especially regarding number of fatal accidents. It would have been preferable to have at least 83 observations for the pedestrian models and about 150 observations for the bicyclist models (Peduzzi et al., 1996).

(10) This study is based on cross sectional analysis, but in such analysis it is difficult to determine causality.

(11) Impact speed has a causal relation with injury severity/outcome, therefore the use of relative fatality risk ratios and a relative fatality risk curve is justified in this case. The relation between the mean travel speed and the injury severity/outcome is much weaker. While higher impact speed results in greater forces that control the injury severity, the mean travel speed does not control the impact speed; it merely correlates with it because there is a probabilistic relation between the mean travel speed, the travel speed of the vehicle involved in an accident, and hence the impact speed. Reduction in mean travel speed will influence the injury risk and the number of serious and fatal accidents only if it influences the driver involved in an accident. It is quite possible that changes in speed limit would influence only those who travel at legal speeds, while those who drive faster would maintain their speeds, in other words, reducing the speed limit would lower the mean travel speed, but the impact speed of the vehicle involved in an accident would not be influenced. In this case, the causal link would be broken, i.e *mean travel speed* $\nsim$ *travel speed of vehicle involved in an accident* ~ *injury severity/outcome*. Therefore, strictly speaking, using relative fatality risk ratios for mean travel speed in this manner is open to criticism. It should therefore not be considered a perfect relation or a flawless methodology but rather a way to gain a better understanding of how the risk of different injury severities/outcomes might be influenced by the mean travel speed. Understanding this relation can aid in the determination of speed policy.

5.2.6 Concluding remarks

The analysis shows that the mean travel speed correlates with the risk of serious and/or fatal injuries for both pedestrians and bicyclists. Furthermore, it shows that serious injuries do occur quite frequently in speed environments where the mean travel speed is below 30 km/h, indicating that, if the goal is to eliminate serious injury accidents, 30 km/h might not be a sufficiently low speed.

5.3 The influence of victim´s age on injury severity/outcome

Previous research has shown that the age of the victim is an important factor in injury severity for both struck pedestrians (Eluru et al., 2008, Henary et al., 2006, Peng and Bongard, 1999) and struck bicyclists (Eluru et al., 2008, Yan et al., 2011). Age has even been shown to be important for the probability of surviving those injuries (Eluru et al., 2008, Henary et al., 2006, Kim et al., 2007, Peng and Bongard, 1999). Age was included as an independent variable in the multinomial logit model presented in section 5.2.1. The age was shown to be statistically significant between minor and fatal injuries, while not statistically significant between serious and fatal injuries. The analysis of datasets 2, i.e. the accident sites where the speed was measured, also shows that the fatal accidents are highly concentrated among senior pedestrians and bicyclists. To gain deeper insight into how age influences the injury severity/outcome, I have used datasets 1, which includes all injury accidents recorded in Sweden for 2004 to 2008 in which a pedestrian or bicyclist was struck, and the victim´s age is known. Figure 47 shows an overview of the proportion of pedestrians and bicyclists who suffered serious and/or fatal injuries by age group.

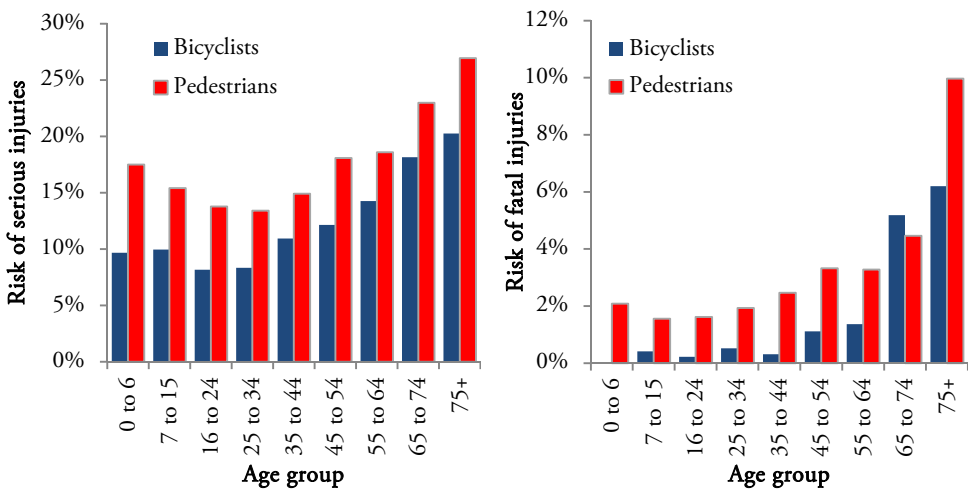

Figure 47: Proportion of serious injuries and fatal injuries for pedestrians and bicyclists struck by motorized vehicles by age group (datasets 1, *paper IV*).

For pedestrians struck by a motorized vehicle, the risk of serious injuries seems to be a U shaped function, i.e. that it is the youngest and the oldest victims that are at the greatest risk of suffering serious injuries. This effect was not observed for bicyclists struck by a motorized vehicle, the youngest bicyclists seem to have similar probability of serious injuries as younger adults. For struck pedestrians, there seems to be a slight elevation in fatality risk for the youngest, and again, the risk of serious injuries

increases with age. This finding may be influenced by the fact that victims in the youngest age groups were struck more often than members of other age groups in places where the speed limit was 30 km/h (15% of children compared to 8 to 13% of other age groups). For struck bicyclists, no elevation of fatality risk is observed among the youngest, while the risk of fatality risk increases with age.

One possible reason why there is no elevation in the risk of serious or fatal injuries for the youngest bicyclists might be that the youngest bicyclists were more frequently struck in low speed environments, were the speed limit was 20 or 30 km/h (18.4% of the age group 0 to 6 and 13.4% of the age groups 7 to 15) compared to adults (between 3.8% and 8.9%), this group had a low involvement rate in accidents with heavy vehicles (1.1% for the age group 0 to 6 years old and 3.0% for the age group 7 to 15 years old, compared to a range of 2.1 to 4.3% for other age groups). Further, the youngest groups had the highest registered rate of helmet use (21.5% for 0 to 6 years old and 13.0% for 7 to 15 years old, compared to 2.1% to 8.7% for other age groups), and the youngest bicyclists are usually kept away from the most aggressive car traffic, given their acknowledged limited cognitive skills for interacting with motorized traffic as bicyclists.

Earlier studies have shown that younger children as pedestrians (Ashton, 1979, Gustafsson and Thulin, 2003, Pitt et al., 1990) and bicyclists (Kaplan et al., 2014, Rivara et al., 1997, Sze et al., 2011) have an elevated risk of serious and/or fatal injuries. There is also considerable evidence in earlier research that the risk of serious and fatal injuries increases with age (Eluru et al., 2008, Henary et al., 2006, Kim et al., 2007, Peng and Bongard, 1999, Sze and Wong, 2007, Yan et al., 2011). What was more unexpected was the finding that there seems to be some sort of 'swap' effect between the two road user groups. The fatality risk for pedestrians increases steadily up to the age group 65 to 74 years old, when it suddenly more than doubles for the age group 75 years and older. For bicyclists however, the fatality risk for the age group 65 to 74 is much higher than that for those aged 55 to 64, while only a minor increase occurs in fatality risk for the age group 75 years compared to that for those aged 65 to 74.

At least three possible explanations might influence this:

(1) As people age, they become more fragile and more likely to sustain injuries (Dehlin and Rundgren, 2007). Since there are some differences between pedestrians and bicyclists in collisions with motorized vehicles, among other that the bicyclists have much higher own speed, this might shift the tolerance threshold for survivability between age groups, i.e. to lower ages for bicyclists. This might partly explain why the fatality risk seems to increase one age group earlier for bicyclists than it does for pedestrians. What contradicts this hypothesis is that if this were true, one would expect the fatality risk for bicyclists to increase further for the age group 75 years and older, an effect not observed in the data.

(2) At certain age, the human body becomes weaker and more fragile (Dehlin and Rundgren, 2007). It is logical that as an individual reaches this point, he or she would stop using a bicycle and become a pedestrian. This means that at some age the weakest bicyclists will become pedestrians, leaving only the strongest and healthiest behind as cyclists. This would result in an accident migration from the bicyclist group toward the pedestrian group, increasing the probability of fatality for the oldest pedestrians, but reducing the probability of fatality for the oldest bicyclists.

(3) It is possible that this phenomenon owes to confounding effects and has nothing to do with hypothesis 1 or 2.

All the hypotheses above are highly speculative.

5.3.1 Limitations

Several of the limitations discussed regarding the analysis of the speed´s importance also apply here:

(1) The results are influenced by underreporting.

(2) The study is based on accident reports, whose quality varies.

(3) Swedish hospitals changes the injury classification from AIS1990 to AIS2005 on the 1st of January 2007; in addition, this part of the study relies on estimates of injury severity from police reports when hospital reports are not available, and the former are less reliable.

(4) The analysis of injury severity/outcome against age might be influenced by other, unobserved effects. In other words, there might be some correlation between the victim´s age and speed environment (partly controlled for in the multinomial logit models; Davis (2001) showed that when controlled for impact speed, the difference in fatality risk against age was strong), helmet use, physical condition, preconditions of the accidents, and so on.

5.3.2. Concluding remarks

This analysis supports earlier findings that age is highly important for injury severity/outcome. Seniors have an elevated risk of serious and/or fatal injuries as pedestrians and bicyclists. Children also show an elevated risk of serious and/or fatal injuries as pedestrians; however, this elevation is not observed for child bicyclists. In addition, there might be some migration effect between senior pedestrians and senior bicyclists that influences the injury risk of those groups, but further study is needed to clarify that relation.

6. Discussion and conclusions

This work focuses on six research questions regarding accidents where pedestrians or/and bicyclists were struck by motorized vehicles. The main focus was to investigate the relation between exposure and risk, and the injury severity/outcome once a pedestrian or cyclist has been involved in an accident (the consequence dimension). This chapter discusses and summarizes the contributions this work makes to answering those research questions.

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(1) What is the relation between the volumes of pedestrians and bicyclists and the number of accidents for those road user groups?

(2) How does the reliability and validity of safety performance functions vary owing to the length of observational periods concerning exposure?

(3) How to interpret the relation between impact speed and injury level of pedestrians struck by motorized vehicles, and what are the implications for speed policy?

(4) What is the relation between the speed environment at the accident site and the injury severity/outcome for pedestrians and bicyclists struck by motorized vehicles?

(5) What is the relation between the age of the victim and the injury severity/outcome of pedestrians and bicyclists struck by motorized vehicles?

(6) What are the differences in injury severity/outcome for pedestrians and bicyclists, struck by motorized vehicles?

6.1 What is the relation between the volumes of pedestrians and bicyclists and the number of accidents for those road user groups?

The first research question adresses the relation between the exposure of pedestrians and bicyclists and the number of accidents with a motorized vehicle that members of those road user groups experience. To investigate this, safety performance functions were created for those two accident types, but in order to gain a deeper understanding of the underlying mechanisms, safety performance functions for single pedestrian and single bicyclist accidents were also created.

The models show that there is a statistical, nonlinear relation between the number of accidents in which pedestrians or bicyclists are struck by a motorized vehicle and the traffic volumes of the respective road user groups (with one exception, the flow of motorized vehicles in the model for struck pedestrians). The number of pedestrians and bicyclists who are struck does not increase proportionally along with the number of pedestrians, bicyclists, or motorized vehicles, i.e. there is a safety in numbers effect for each group. This finding aligns with those of earlier studies (Brüde and Larsson, 1993, Elvik, 2009a). Furthermore, the models show that the number of accidents between pedestrians or bicyclists and motorized vehicles increases as the volume of motorized vehicles increases, given that the number of pedestrians and bicyclists is kept constant. Again, this is consistent with earlier studies (Brüde and Larsson, 1993, Elvik, 2009a). Several possible explanations exists, but focus is often on behavioral adaptation.

More unexpected was that a safety in numbers effect was observed for single pedestrian accidents. It is more difficult to see why the presence of more pedestrians should result in their adapting behaviours so that the risk of a single pedestrian accidents decreases. Though the possibility cannot be dismissed that this might be an effect of learning (the presence of more pedestrians might suggest that people travel more as pedestrians and therefore gain skills to travel more safely). Perhaps, a more probable explanation would be that the safety in numbers effect for single pedestrian accidents partly reflects the quality of the infrastructure and its maintainance (or some of the other theories discussed before), which often relate to the exposure of pedestrians (or other relevant road user groups). Therefore, if the safety in numbers effect for pedestrians can partly be attributed to the infrastructure´s quality or some of the other theories discussed earlier, it is possible that those factors are more important for other accident types as well (e.g. collisions between motorized vehicles and pedestrians/bicyclists) and that the contribution of behavioral adaptation is perhaps not as great as previously believed (e.g. Jacobsen, 2003). This requires further research.

Because of several country specific factors, accident models cannot be blindly applied across various countries (or regions, for that matter). This study contributes a new safety performance functions for pedestrians and bicyclists struck by motorized vehicles at intersections in Sweden, based on comprehensive site observations (three hours per site) and based not only on police reported accidents, but also on hospital reported accidents (registered in STRADA). This should make the models considerably more reliable since there is greater underreporting when the accident data is only based on the police reported accidents (Jonsson et al., 2011). Second, by creating comparable safety performance functions and identifying a safety in numbers effect in all the different accident models, even though the explanations commonly cited for this effect do not apply to all those accident types to the same extent. This may indicate that when explaining the causes for the observed safety in numbers effect in accident models, too much focus is placed on behavioral adaptation; perhaps other possible explanations should be explored.

6.2 How does the reliability and validity of safety performance functions vary owing to the length of observational periods concerning exposure?

The second research question investigates the possible influence of an observation period´s length on the reliability and validity of the accident models. In order to answer this question, I created several safety performance functions based on observational periods of varying lengths, both parsimonious models (based only on the exposure variables) and fully specified models (geometric variables included based on sensitivity analysis). Doing so simulated what would have occurred if the study had been performed several times using observational periods of different lengths. This allowed for testing the validity and reliability of the models, at least indirectly.

The results showed that the safety performance functions based on short observational periods were unreliable and did not have validity compared to the model based on 3 hours of observation per site, though they were within the confidence intervals of the base model. Furthermore, the analysis showed that the most reliable or most valid models did not show any considerable improvements in the statistical measures (commonly used to estimate model quality) over models based on shorter observational periods. Hence, the statistical measures for models based on short observational periods might give the researcher a false sense of confidence regarding the model. The researcher must therefore carefully weigh the benefits of a model with many observational sites based on short observational periods versus one with a few sites based on longer observational periods. Since measuring traffic is resource demaning, the former option might allow testing for the influence of many

variables if the site selection is appropriate, thereby controlling for confounding factors. This would, however, be done at the cost of vaguer estimation of exposure´s importance. The latter option gives a more reliable estimation of exposure´s importance, but more resources are used per site, and that might result in fewer sites; hence, the data might not allow the inclusion of and controlling for as many geometrical variables.

I have considered how the estimation of exposure itself would vary based on how long the observational periods are. The results show that reliability increases with longer observations, as expected. The results do not suggest, however, some optimal length for observations; rather, observational periods´ length must be determined according to how much measurement error is acceptable. The results also indicate that perhaps it would be more suitable to choose the length of observational periods based on how many road users there are, i.e. places with higher exposure can be measured with shorter observations than places with low exposure can; or a combined critiera might be used, one of two critierias must be fullfylled: some given number of road users or some given time period.

The study addressed this research question by examining how much influence the length of an observational period has on the validity and reliability of safety performance functions. This provides improved insights into the methodological aspects of such studies and highlights the importance of considering not only the statistical significance of accident models, but also the reliability of the independent variables used to estimate those models. To my knowledge, this is the first time these factors have been tested in this manner.

6.3 How to interpret the relation between impact speed and injury level of pedestrians struck by motorized vehicles, and what are the implications for speed policy?

The third research question explores ways to interpret fatality risk curves for pedestrians struck by motorized vehicles based on impact speed. To investigate this relation, a new model was created, namely, the relative fatality risk curve, which better describes how changes in impact speed influence the number of fatal accidents.

This research explores why recent fatality risk curves differ so drastically from the findings of earlier studies, showing that the difference arises most likely because the earlier studies were based on biased data, and their analysis did not take that into consideration. When one of the older fatality risk curves is scaled for the bias in the study´s data and compared to recent studies (Richards, 2010), there is limited evidence that the fatality risk is substantially lower at urban speeds than it was before.

It is, however, challenging to compare fatality risk values across two independent studies since there might be confounding effects which might hide the real change. Furthermore, I have demonstrated that it is theoretically almost impossible to determine the actual universal fatality risk and that changes or differences between studies likely owe to methodological differences, inclusion critiera, and population variations between one region or country and another, for example the age distribution of the populations (e.g. Henary et al., 2006) and differences in vehicle fleets (e.g. Desapriya et al., 2010).

Finally, the analysis suggests three perspectives from which to interpret the fatality risk curves: the individual perspective, the system perspective, and the number of accidents perspective. Applying the individual perspective to the fatality risk curve is not likely to provide an accurate impression about the importance of impact speed (or speed in general) for injury severity/outcome, because the fatality risk is generally low at urban speeds and the risk models, usually S curves, give a strong visual perception that is somewhat false. For that purpose, it is better to use the system perspective, with some focus on where the accidents occur (number of accidents perspective). Hence, despite the known limitations of that approach, it is preferable to use relative risk values or relative fatality risk curves instead of absolute risk values.

The relative approach shows, theoretically, that the number of fatal accidents (and the probability of fatal injuries) is highly sensitive to changes in the impact speed and that there is no safe speed. Furthermore, again theoretically, the influence that speed changes have on the number of fatalities is almost independent of the original speed (in urban speed environments). This means that even though the fatality risk curve seemingly shows lower fatality risk at low speeds than at higher speeds, it does not suggest that the fatality risk or the number of fatalities is less sensitive to speed changes at those lower speeds (observe, however, that speed also influences the risk of an accident occurring in the first place). Finally, a mathematical computation shows that the relative fatality risk curve is fairly reliable, see *paper II*, in other words we can expect that the absolute fatality risk compared to impact speed will differ between studies and perhaps even between time periods, but the relative fatality risk should remain fairly robust. Until there is more evidence to adjust the form of the fatality risk curves, or to determine whether there is in fact some absolute speed below which no one will die, then the main results of fatality risk curves and relative fatality risk curves are as follows:

There is no safe speed; a lower impact speed will most likely result in fewer fatalities, and a higher impact speed will most likely result in more fatalities.

Nevertheless, it is important to consider that the number of serious and fatal injuries is highly related to the risk of being involved in an accident, a risk that is influenced

by vehicle speed. Therefore, if the aim is to determine some safe speed, then a combination of the two dimensions, risk and consequence, is necessary.

This study addresses the research question by explaining why the fatality risk curve has changed so drastically and by improving the understanding of the implications those results have for views about the importance of speed and speed changes for the injury outcome in traffic accidents. Furthermore, I have suggested three interpretive perspectives: (1) the individual perspective, (2) the system perspective, and (3) the number of accidents perspective; that apply the knowledge found in fatality risk curves and similar data as a basis for decisions regarding speeds.

6.4 What is the relation between the speed environment at the accident site and the injury severity/outcome for pedestrians and bicyclists struck by motorized vehicles?

The fourth research question investigates the relation between the speed environment at the accident site and the injury severity/outcome for struck pedestrians and bicyclists.

The analysis showed that serious injury accidents frequently occur in low speed environments (mean travel speed below 30 km/h) for both struck pedestrians and struck bicyclists. This might indicate that in order to prevent serious injury accidents, 30 km/h might not be a sufficiently low speed. Moreover, the data might suggest that fatal accidents are rare where the mean travel speed is below 40 km/h, and that serious injuries are rare when the mean travel speed is below 20 km/h, but the study is based on too few accidents to conclude if it is so. That those injury severities are rare below these two speeds likely reflects the combined influence of the fact that injury severity is lower at those speeds and that the risk of an accident occurring at all is lower.

Mathematical modelling showed that the risk of fatality for struck pedestrians and bicyclists appears at somewhat higher speeds when modeled by speed environment than it does when modelled by impact speed. This was expected, since many drivers manage to brake before a collision occurs; hence, the impact speed is generally lower than the travel speed (e.g. Anderson et al., 1997). These models also show that there is a statistical relation between the mean travel speed and the probability of serious or fatal injuries. Comparing the models to the raw data (i.e. injury severity/outcome against speed limit) showed quite a good fit in urban speed settings. In addition, the model showed a relatively good fit when compared to the consequence dimension of the power model, but since there are fundamental differences between those models and the models in this thesis, they naturally do not fit perfectly.

Since my models show a very low fatality risk at urban speeds, it can be difficult to interpret and apply the individual perspective on them; it is difficult to perceive the implications of the low fatality risk or to understand how important speed changes are. Even so, these models are informative from a system perspective. It is also worth mentioning that many accidents result in serious or fatal injuries but are not neccessarily related to the speed of the motorized vehicle, e.g. run over accidents, a bicyclist who strikes a stopped vehicle (which however should be highly related to the speed of the bicyclist). Those accidents must be dealt with in manners other than adjusting speed and speed policy.

This study contributes to answering this research question by investigating the relation between mean travel speed and the injury severity/outcome for struck pedestrians and bicyclists; resulting in (among others) mathematical models to describe this relation. Ultimately, more clearly understanding the relation provides an improved understanding of the speed environments in which accidents do occur and of the importance of mean travel speed to the injury severity/outcome. To my knowledge, this relation has never before been investigated in this manner.

6.5 What is the relation between the age of the victim and the injury severity/outcome of pedestrians and bicyclists struck by motorized vehicles?

The fifth research question investigates the relation between the age of the victim and the injury severity/outcome for pedestrians and bicyclists struck by motorized vehicles.

The mathematical models show that age is influential for the injury severity/outcome of struck pedestrians and struck bicyclists, but most of those who were fatally injured were seniors. Analyses of the larger datasets (datasets 1) showed that senior pedestrians have an elevated probability of suffering serious or fatal injuries; however, seniors are not alone in facing an elevated risk of serious injuries. Rather, the risk of injury is continuously increasing with age, beginning with the youngest adult groups. The data also show that child pedestrians have an elevated risk of serious or fatal injuries; the risk function compared to age therefore seems to be a U function, a finding that partly aligns with earlier research (e.g. Eluru et al., 2008, Gustafsson and Thulin, 2003, Henary et al., 2006, Peng and Bongard, 1999, Pitt et al., 1990), but some studies did not identify elevated risk for the youngest and some were only focused on children and therefore obviously could not investigate the risk for seniors.

The dataset for cyclists showed similar effects for seniors, who have an elevated risk of serious or fatal injuries; however, no elevation in risk of serious or fatal injuries was

observed for children as bicyclists. Earlier studies have shown that the youngest bicyclists and/or senior bicyclists to have elevated risk of serious and/or fatal injuries (e.g. Eluru et al., 2008, Kaplan et al., 2014, Rivara et al., 1997, Yan et al., 2011). Possible reasons for why this elevation among the youngest bicyclists is not observed in the data are that child bicyclists are often kept away from the most aggressive car traffic, owing to parental concerns regarding their safety and cognitative ability to interact with the motorized vehicles as bicyclists; or that the elevation observed in earlier studies is partly due to that those studies also included single road user accidents. This requires further research.

Comparing the injury severity/outcome for struck pedestrians and struck bicyclists draws out interesting pattern. The fatality risks seems to start to increase at lower ages for bicyclists than for pedestrians, and there seems to be some crossover effect, wereby the increase in injury severity/outcome is not as great for the oldest as it is for the second oldest group. This is discussed in section 6.6.

My contribution to addressing this research question was to examine the risk of serious or fatal injuries for a comprehensive dataset, comparing risks for struck pedestrians and struck bicyclists. This approach provides a better understanding of which groups are most fragile and require special attention when considering speed policy; further, I have identified some crossover effects, though those require further research.

6.6 What are the differences in injury severity/outcome for pedestrians and bicyclists, struck by motorized vehicles?

The sixth research question draws out the differences in injury severity/ outcome for pedestrians versus bicyclists struck by motorized vehicles.

The literature review revealed several differences between pedestrians and bicyclists, in a collision with a motorized vehicle, see discussion in *paper IV*. The analysis showed that while mean travel speed, age (and vehicle type for bicyclists, though it was not statistically significant in the models presented in this study) are important factors affecting the injury severity/outcome for both groups. The effects differ considerably between those groups. Bicyclists are less likely to suffer fatal injuries, but greater part of the serious injuries occur in low speed environments. Fatal pedestrian accidents mainly occur where the mean travel speed is between 40 and 50 km/h, while fatal bicycle accidents occur over the whole speed spectrum, from 25 to 90 km/h. This finding bears some implications for speed policy: it is possible to influence the great majority of fatal pedestrian accidents by focusing on urban areas with 50 km/h speeds, whereas the same focus would affect only a small proportion of the fatal bicycle accidents.

The age analysis showed that the increase in the risk of serious injuries with age was similar for both pedestrians and bicyclists. However, in the fatal injuries an interesting pattern arises. The fatality risk for struck pedestrian spikes in the age group 75 years and older, while there is not such a great difference between the age group of 55-64 and 65-74. For bicyclists however, great differences appear between the age groups 55-64 and 65-74, whereas only a minor increase appears in the age group 75 years and older. This cross over effect is somewhat unexpected, and even though these data do not support an explanation for this, they do permit speculations about possible causes. The human body becomes more fragile with higher age (Dehlin and Rundgren, 2007), hence, the victim will suffer more serious injuries and is more likely to die from those injuries. Bicyclists travel at higher speeds than pedestrian do, a factor that might explain why the fatality risk spikes earlier for them than for pedestrians. If all other factors remain constant, this idea suggests that the increase in fatality risk should be even greater for the oldest group of bicyclists, but this is not the case. The trend could also possibly be explained by some migration effect between bicyclists and pedestrians. When a bicyclist feels that he or she has become more fragile because of high age, he or she might choose to stop bicycling and start walking more. This would leave the strongest as bicyclists, reducing the risk of fatality for bicyclists and increasing the risk of fatality for pedestrians. If this effect exists for fatal accidents and the oldest age group, one can hypothesize whether this effect might start at lower ages or even be apparent for serious injuries. It must also be acknowledged, however, that this effect might be a consequence of some unobserved confounding factor.

Only a handful of published studies use comparable datasets for pedestrians and bicyclists (e.g. Maki et al., 2003). By examining both struck pedestrians and struck bicyclists, this study contributes to an understanding of how the situation differs for those groups and facilitates the identification of possible cross over effects or migrating effects that might influence how the injury risk values of various road user groups are perceived.

6.7 Method discussion and limitations

6.7.1 Study I

The first study investigates the relation between exposure, measured as daily flows, and the number of accidents. First of all, it is possible that it is in fact not the exposure, as daily road user flows, that influences the number of accidents, but rather the flows at the time of the accident that do so (Mensah and Hauer, 1998) It is also

possible that it is the number of events that have a probabilistic relation to the risk of an accident occurring (Elvik, 2014a). There are practical reasons why daily flow variables are used, but it can be difficult to collect data on the traffic flows at the time of an accident. The reason is that the exposure measure for the time before the accident occurs or at the precise moment of the accident is the one of interest. As soon as the accident occurs the flow, or exposure, is interrupted by the accident, and the flow situation changes (Zheng et al., 2010). Therefore, one must use exposure measures that are, in fact, proxy variables for the exposure at the time of the accident (such as a measure of annual average daily traffic, or the exposure measured at a similar time and day as those when the accident occurred). The idea behind this approach is that there should be some correlation between those measures and the flow at the time of the accident. Another approach might be to perform continuous proactive counting of road users flows. Then when an accident occurs, these data would be analyzed for the times before the accident and related to the accident. This has been done for accidents on motorways (Martin, 2002). Although, proactive counting like this might be difficult for vulnerable road users, new technology is emerging, including both external observational equipment (counting with video analysis) and black-boxes that internally collect data for cars (perhaps in the future even for bicyclists, through smart phones or units installed in bicycle helmets or on the frame of a bicycle), that might allow this approach, thereby collecting flows in real time, accident specific, and perhaps even with exposure as an even based measure. This might be the next step in developing safety performance functions to relate traffic flows to the number of accidents; it is certainly a substantially more direct approach than estimating traffic flow; and, hence, a superior approach that would result in stronger data.

Secondly, observations for this study were performed during off peak hours in order to avoid problems with the scaling process. From a methodological perspective, this is interesting if the proportion of exposure during the observational period differs between sites, for that might influence the scaling process. Given that the exposure variable is only a proxy variable, however, and not an estimate of the real flow situation at the time of the accident, I believe that the measurement error caused by this approach is less than the measurement error caused by using this proxy variable, considering that my results showed the reliability and validity of the models varying with the length of the observational period. However, as with all statistical models, one must recognize that the model is an estimation and is vulnerable to numerous measurement errors.

Thirdly, this study is based on cross sectional data, and the difference in design was controlled for by using geometric variables. This approach results in difficulty in determining anything regarding causality. The observed effects (e.g. safety in numbers) may owe to unobserved confounding factors, and it is difficult to decide whether the effect is truly safety in numbers or for example numbers in safety (in which road users choose safer locations in greater extent).

Finally, Kulmala (1995) discusses that creating a safety performance function can be challenging if the mean number of accidents per site is below 0.2. Even though our data fullfill this criterion, the number of sites is quite low, and the reliability of the results could be improved by expanding the data.

It is recommended that the counting of pedestrians for single accidents also include the number of pedestrians who crossed a street. Also, in order to study whether the safety in numbers effect is in fact causal, it is necessary to perform before and after studies – possibly complemented by conflict studies, so as to counteract the limitation of accident analysis where the number of accidents is heavily influenced by random variation.

6.7.2 Study II

The second study focused on the importance of the speed environment (mean travel speed), and on the ways this might be used to help reduce the number of serious and fatal accidents. The relation between mean travel speed and the injuries sustained is indirect, that is, it is not fully causal. The driver involved in the accident was perhaps driving extremely slowly or very fast; therefore, the mean travel speed might not be representative for the accident which might break the logical link between the mean travel speed and injury severity/outcome. This means that the relation is more correlative or probabilistic than causal; at least, it is only indirectly causal. Newertheless, there should be (and this is supported by the results in this thesis) some logical relation between mean travel speed and injury severity/outcome. Since speed is controlled through the speed limit and the mean travel speed, then despite the model´s limitations, those models constitute a valuable addition to the tools for understanding the importance of speed for safety, though one cannot state that a change in mean travel speed will automatically result in less severe injury severity/outcomes. Injury severity/outcome can be reduced only if the changes in mean travel speed results in the travel speed of the vehicle involved in a collision to be lower.

This is a cross sectional study; hence, as with the safety performance functions, it is difficult to determine whether the relation owes to correlation or causation and whether it is vulnerable to confounding factors. The data certainly show some correlation, and there is a logical link indicating a causal (if indirect) relation. Despite this, it provides valuable insight into the importance of the speed environment for the injury severity/outcomes in accidents. Another limitation is that the datasets for the multinomial logit models are rather small. Peduzzi et al. (1996) suggested that the minimum number of cases should be 10 times the number of independent variables divided by the proportions of the smallest group in the data. In this case the figure is 83 pedestrians (my data included 79 cases) and 154 for bicyclists (my data include 77

cases, had the vehicle type been excluded then the rule of thumb would suggest minimal of 103 cases). This study was limited by the number of accidents that occurred and that it is resource demanding to perform field measurments. However, these models would benefit from more extensive data, especially the model for bicyclists. Therefore, caution might be in order regarding the size of the effects of the independent variables (i.e. speed, age, and vehicle type).

6.8 Practical implications

The work to prevent traffic accidents is highly important and closely related to the traffic planning process. Caution is needed, of course, because much remains to be learned regarding the relations discussed here, but the practical implications of the study results certainly merit discussion. What is, their role in traffic planning and setting priorities in designing infrastructure and choosing speed policy?

The practical implications can be divided into two categories: those pertinent to scientific methods and those pertinent to traffic policy, planning and design.

6.8.1 Scientific and methodological implications

Study 1 showed that the length of the observational period has a considerable influence on the reliability and validity of the safety performance functions; significant improvements arose if the observational period was extended, even though it was within the 95% confidence interval of the base models. Furthermore, the study demonstrated that even though the validity and reliability improved, this was not apparent in most of the goodness of fit parameters. The researcher must therefore consider separately how reliable the measurement of the explanatory variable is, because the model´s statistical parameters will not necessarily reveal whether the explanatory variables are reliably estimated. Analysis of the counts did not show any optimal length for an observational period, only that longer periods provides a more reliable estimation of the exposure. Therefore, the researcher must determine how much uncertainty is acceptable for the topic at hand. The results do show, however, that the length of the observational period should perhaps not be fixed but take into consideration how great the exposure is; or employ a combination of these two approaches. A count at a location characterized by higher exposure will probably provide a better estimation of the exposure than a count at a location with low exposure.

Study 2 presented a new approach, attempting to analyze the relation between mean travel speed and the injury severity/outcome. Though this approach has some limitations (owing to, among other things, the weak causal link between mean travel

speed and injury severity/outcome), it works to bridge the gap between the individual vehicle´s speed and the overall traffic speed, so that the information can be used for policy purposes. The approach proved to be usable and can be applied in large scale studies.

6.8.2 Traffic policy, planning and design implications

Study 1 showed three different effects:

(1) The risk per pedestrian and bicyclist is lower at locations with high exposure of pedestrians or bicyclists compared to locations with low exposure of pedestrians or bicyclists.

(2) The number of pedestrian and bicyclist accidents is higher if the number of motorized vehicles is higher.

(3) The risk per motorized vehicle is lower at locations with high exposure of motorized vehicles compared to locations with low exposure of motorized vehicles.

The total effect on the number of accidents therefore reflects a combination of the exposure of pedestrians, bicyclists, and motorized vehicles. This finding aligns with those earlier studies have found (Elvik, 2013a). It is unclear, however, whether this is a causal effect of exposure or partly an effect of other mechanisms. The results in this thesis might suggest that the safety in numbers effect owe more to correlation with infrastructure quality and maintenance, or some of the other factors discussed before, than previously believed; even though behavioral adaptation is probably also an important factor behind the phenomenon.

From the practical perspective, this trend suggests that in order to prevent collisions between pedestrians or bicyclists and motorized vehicles, it might be advisable to put special focus on locations characterized by high traffic volumes of both motorized vehicles and pedestrians or bicyclists. Both the models presented in this study and earlier ones (Elvik, 2009a) suggest that an increased flow of motorized vehicles correlates with a higher number of accidents. Given that it is likely that there is a relation between infrastructure quality and maintenance, and given that this idea is supported by earlier research (Elvik and Vaa, 2004), focus should be not only on increasing the exposure of those groups, but rather on combining increased exposure with improved infrastructure quality and maintenance, thereby harvesting all the effects that are likely to improve the safety of pedestrians and bicyclists.

If we allow us for the sake of argument to assume for a moment that the relation between exposure and number of accidents is fully causal; that increased exposure will reduce the risk per road user (this is only a hypothetical example so that we may reflect over what the practical implications of a "true" causal safety in numbers effect

would be, for example behavioral adaptations; the safety in numbers effect is likely to be contribution from several mechanisms, some that are causal like behavioral adaptations, while others that are not causal like numbers in safety). This suggests that there are some benefits to increasing the number of pedestrians and bicyclists, since the marginal increase in number of accidents reduces. However, the influence of this change on the total number of accidents depends on if the increase owes to new road user or due to modal shift. If those pedestrians or bicyclists are new road users, the number of pedestrian and bicyclist accidents will increase. On the other hand, if the increase in pedestrians and bicyclists ows to a modal shift, whereby these individuals previously travelled in motorized vehicles, one can expect accident migration from motor vehicle accidents (i.e. reduction in accidents involving motorized vehicles, not included in those calculations) toward bicyclist and pedestrian accidents. There will also be an additional effect, whereby the reduction in motorized vehicles will decrease the risk per vulnerable road user of being involved in an accident (as in statement 3, the risk per pedestrian or bicyclists increases with increased number of motorized vehicles).

For example, according to the models in equations 10 and 11, if the volume of pedestrians/bicyclists is 100 and the volume of motorized vehicles is 1 000. 10% of the motorized vehicle operators become pedestrians/bicyclists (resulting in a 100% increase in those road user groups), this would result in a 37% (pedestrians) and a 25% (bicyclists) increase in the number of accidents for those road user groups. If those 100 extra pedestrians/bicyclists were new road users (the motorized traffic is unchanged at 1 000) then the increase would have been 46% (pedestrians) and 34% (bicyclists). In other words, a modal shift might not result in the same increase in number of accidents as new cyclists. Further, the presence of more pedestrians or bicyclists might influence the travel speed[14] which is strongly related to the risk of being involved in an accident, which can be expected to further reduce the accident risk. Those values are, of course, dependent on absolute volumes, and using those models this way cannot be considered to be accurate since this use is only valid if the relation between exposure and the safety in numbers effect is in fact a fully causal effect, a requirement that has not been confirmed. Nevertheless, even though this example is oversimplification, given that it is likely that this relation is not fully causal, this example demonstrates an interesting tendency, and what might be the practical implications of the fact that the motorized vehicle contribute to the accidental risk.

[14] Travel speed is related to the risk of an accident occurring. Therefore, if travel speed correlates with exposure, it can be speculated that the speed might be a contributory factor in the safety in numbers effect. However, since speed frequently correlates with other contributory factors, it is challenging to include it in the modelling process (Jonsson, 2005). This requires further research.

Study 2 shows some results that are of interest for both infrastructure design (to control the speed) and speed policy. Since speed is very important for injury severity/ outcome, an appropriate speed needs to be identified, one that will minimize health loss while maintaining an effective transport system. But what is an appropriate speed for urban settings? Based on the findings of this study, I cannot identify any safe speed; I note only that a lower speed reduces the probability of serious or fatal injuries and that a higher speed increases the probability of serious or fatal injuries. The data show that fatal accidents are relatively rare when the mean travel speed is below 40 km/h, and serious injuries are rare when the mean travel speed is below 20 km/h, while a considerable part of the serious injury accidents occur in places where the mean travel speed is between 20 and 30 km/h. Furthermore, the results show that seniors and children are more likely to sustain serious and/or fatal injuries as pedestrians in collisions with motorized vehicles. Finally, most fatal pedestrian accidents occur in places where the mean travel speed is between 40 and 50 km/h and where the speed limit is 50 km/h (possibly because most of the urban road network has a speed limit of 50 km/h). From these findings, three preliminary recommendations might be suggested for locations where there is a risk of accidents between pedestrians or bicyclists and motorized vehicles:

(1) The presence of seniors or children increases the importance of having lower speeds or of taking some other measures to ensure their safety. It is my view that the design process should focus on the weakest, as they have the same right as others to use the road system without risking health loss.

(2) Most fatal pedestrian accidents occur in 50 km/h speed environments. Therefore, to maximize the reduction in the number of fatal accidents, it might be advisable to consider to focus on reducing the speed in today´s 50 km/h areas where there is a lot of interaction between pedestrians/bicyclists and motorized traffic. Given that fatal accidents seem to be rare when the mean travel speed is below 40 km/h, this might be a good starting point. But this approach should also consider in terms of cost-and benefits (i.e. how great an area is behind each accident in 30 km/h versus 50 km/h areas) and even in terms of the risk dimension (since travel speed influences the risk of accidents occurring in the first place).

(3) To achieve Vision Zero, i.e. to eliminate all serious (and fatal) injuries, the aim should initially be to reduce the speed to 20 km/h in sensitive traffic environments, where pedestrians and bicyclists interact with motorized vehicles, as serious injuries seem relatively rare at speeds below that. This is suggestion is further supported by earlier research, where no individual suffered serious injuries (AIS3+) when the impact speed was below 20 km/h (Ashton, 1978).

I further suggest that when applying injury risk curves, one use the relative approach from a system perspective and consider where the accidents occur (i.e. the number of accidents perspective).

6.9 Transferability of results

The safety performance functions are based on Swedish data, and since there are several factors influence the relation between exposure and the number of accidents, the transferability of the models presented here is low. The tendencies, however, i.e. safety in numbers for all three road user groups, low validity and reliability for models based on short observational periods etc. should prove transferable, but several prior studies have shown the safety in numbers effect (see Elvik, 2009a). We however, cannot assume that the level of such effects will be the same in any given country.

The relation between impact speed and injury severity/outcome is controlled by the laws of physics. If the vehicles, pedestrians or bicyclists and the accident mechanisms are similar, then the risk of serious or fatal injury should be similar, independent of country. But since all those variables (e.g. vehicle type, age composition of the population) vary between countries, the physical link, hence the transferability of the results and models is weaker. This became clear in the literature study in *paper II*, where the fatality risk varied extensively between studies. The analysis in *paper II,* however, showed that when applying a relative approach, specifically, a relative fatality risk curve, to the unreliable fatality risk curves, the model was more stable. In other words, relative injury risk curves are more stable and more reliable than absolute injury curves are. The relative approach is nevertheless still sensitive to other limitations, such as the fact that the form of the absolute fatality risk curve might differ from one´s assumptions about it. For an injury risk curve to be representative for certain populations or generalizable for another region (e.g. Sweden), it must fulfill some requirements:

(1) The data, which are usually stratified with regard to injury severity/outcome, must be weighted to render them representative of the actual risk of injury among the population.

(2) The accident data must be based on a population that shares certain similarities with the population it is meant to represent, e.g. age distribution, vehicle fleet, health and emergency care, the degree of underreporting, response times etc.

Caution is advisable if the absolute fatality risk values are to be transferred to another country. In that case, the two countries should be compared to determine whether the other influential factors are similar.

Regarding transferability of the models for risk of serious and fatal injuries to mean travel speed, there are some aspects that needs to be acknowledged: (1) The models would benefit from more observations to get a more reliable assessment of the size of the relations. (2) For the model to be valid for other locations requires that the whole process, from the normal travelling towards the resulting injury severity/outcome to be compatible between the sites the models are based on and the site the model is to be used on. The requirements for this relations for the impact speed (i.e. what occurs after the point of collision) was described here above, however, it remains to discuss what occurs before the impact. For the transferability, the relation between the mean travel speed, the travel speed of the vehicle involved in the accident and the braking maneuvers needs to be similar. It is likely that there are some differences between countries (and even locations), both because of different traffic situations and traffic ´cultures´, that might possibly influence how the risk of accident involvement will vary dependent on the speed of the individual vehicle compared to the mean traffic speed. We can also expect differences caused by different vehicle fleets and how much braking will occur; hence, how the travel speed influences the impact speed, might be influence by the vehicle´s properties. Despite this, it is likely that the main relation, that there is relation between mean travel speed and injury severity/outcome, will be correlated (through the probabilistic relation discussed before), however, caution is in order regarding the size of this relationship, since it might vary between regions.

6.10 Concluding remarks and further research

The findings of this study have increased the understating of, on one hand, relations between exposure and the number of accidents, and, on the other hand, the importance of speed and the speed environment to the injury severity/outcome. The main conclusions are:

(1) There seems to be a safety in numbers effect for accidents between pedestrians and motorized vehicles and for accidents between bicyclists and motorized vehicles. This safety in numbers effect is apparent both from the perspective of pedestrians and bicyclists, and from the perspective of motorized vehicles.

(2) The length of observational periods has considerable influence on the reliability and validity of safety performance functions (even though it was within the 95% confidence interval of the base models), without showing that influence in the statistical parameters, commonly used to verify that the models are reliable.

(3) The length of observational periods should take exposure into consideration; less time is required to assess the exposure at locations with high exposure than at those sites with lower exposure.

(4) The fact, that the new absolute fatality risk curves against impact speed show lower fatality risk at urban speeds is mainly because the new curves are controlled for a stratified sampling technique. There are three options available for interpreting those curves for speed policy: the individual approach, the system approach, and the number of accidents approach. The individual approach has several disadvantages, and this work suggests that the system approach is more appropriate.

(5) The fact, that new fatality risk curves seem to indicate that the risk of fatality is lower than previously thought does not suggest that the speed can be raised. This is mostly a visual illusion and the number of accidents is just as sensitive to speed changes as it was believed to be in the past.

(6) A considerable proportion of serious injury accidents occur in low speed environments (mean travel speed below 30 km/h), indicating that 30 km/h might not be a sufficiently low speed limit for achieving Vision Zero.

(7) There is a statistical relation between mean travel speed and injury severity/outcome for pedestrians and bicyclists struck by motorized vehicles.

(8) The age of the victim is highly important for injury severity/outcome. Seniors have an elevated risk of serios or fatal injuries, as do children as pedestrians. The risk curve therefore seems to be U shaped against age for pedestrians.

(9) There might be some migration effect between senior pedestrians and bicyclists, where the risk changes with age differences between pedestrians and bicyclists.

The results also highlight several research gaps that could not be addressed in this project and that require further study:

(1) The safety performance function showed an unexpected nonlinear relation between exposure and single pedestrian accidents, i.e. safety in numbers effects. This might reflect biased underreporting or indicate that the safety in numbers effect has been too readily attributed to behavioral adaptations. Clarifying this relation requires a large scale detailed study to investigate how different factors or effects contribute to the safety in numbers effect for single pedestrian accidents and for all accident types.

(2) It would be interesting to investigate how risk (against exposure) differs according to whether bicyclists have the right of way against the flow of motorized vehicles they are crossing.

(3) This study demonstrates interesting relations regarding speed environment and injury severity/outcome. However, a large scale, independent study might be in order to confirm the results and to better determine the extent of this relation.

(4) There might be some theoretical speed, below which no serious injury or fatal accidents take place, owing to the combined influence of low risk and low probability of fatality if involved in an accident (excluding run over accidents). Exploring this possibility would require a large scale study.

(5) This study, and earlier ones investigates the relation between *impact speed ~ injury severity/outcome, travel speed ~ injury severity/outcome* and *mean travel speed ~ injury severity/outcome*. Further research is required to determine what occurs between the travel speed and impact speed of the vehicle involved in an accident (e.g. whether reactions, braking, and evasive maneuvers are related to the vehicle´s initial travel speed); and the relation between the speed distribution and the travel speed of the vehicle involved in an accident (e.g. can we find any relation regarding if vehicles driving above mean travel speed, or driving at the 95 percentile speed towards the injury severity/outcome).

(6) The analysis suggests that there might be some migration effect between pedestrians and bicyclists, that could influence our understanding how the risk of serious or fatal injuries changes with age. Three possible explanations were discussed; however, those hypotheses are speculative. and both the effect and the hypotheses require further investigations.

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Appendix A: Parameters and statistical properties of Poisson models

To approximate the proportion of expected systematic variation explained, Poisson models were created based on the same variable set as the negative binomial models. The parameters of those models, and statistical properties are shown in table A.1 (parsimonious models) and A.2 (fully specified models).

Table A.1: Parameter estimations for the parsimonious Poisson base models (β_i). The standard error are within the parenthesis.

	Variables	Model i	Model ii	Model iii	Model iv
	Intercept	-5.952	-7.281	-12.944	-10.781
		(1.087)	(1.275)	(3.356)	(2.020)
Exposure variables	Pedestrian flow	0.583		0.556	
		(0.190)		(0.217)	
	Bicyclist flow		0.677		0.422
			(0.172)		(0.147)
	Motorized vehicle flow			0.651	0.639
				(0.350)	(0.264)
	Scaled deviance	100.155	96.058	65.337	129.348
	Proportion of systematic variation explained:	0.421	0.810	0.943	0.703

Table A.2: Parameter estimations for the fully specific Poisson base models (β_i). The standard error are within the parenthesis.

	Variables	Model i	Model ii	Model iii	Model iv
	Intercept	-4.762 (1.231)	-5.121 (1.205)	-12.722 (4.169)	-10.376 (2.447)
Exposure variables	Pedestrian flow	0.437 (0.204)		0.327 (0.246)	
	Bicyclist flow		0.361 (0.183)		0.352 (0.167)
	Motorized vehicle flow			0.629 (0.483)	0.636 (0.298)
City*	Helsingborg/Kristianstad	0	0		
	Eskilstuna/Västerås	-1.079 (0.798)	-0.309 (0.629)		
	Kalmar/Halmstad	-1.511 (0.719)	0.197 (0.413)		
Traffic environment	Arterials		0.294 (0.563)	-0.571 (0.737)	
	Central		0.037 (0.405)	-0.649 (0.611)	
	Rural/Industrial		-1.784 (1.052)	-1.286 (1.177)	
	Residential		0	0	
Traffic control	Traffic signal		0.379 (0.511)	0.976 (0.693)	0.130 (0.379)
	Right of way/Yield/Stop sign		0	0	0
Speed limit	30-40 km/h			1.658 (1.055)	0.119 (0.363)
	50 km/h			1.116 (1.098)	0.376 (0.322)
	60-70 km/h			0	0
Sight conditions	Good		-0.235 (0.351)		--0.494 (0.293)
	Average/Poor		0		0
Bicyclist integration with car traffic	Fully integrated				0.355 (0.450)
	Partly integrated				-0.035 (0.289)
	Fully segregated				0
	Scaled deviance	92.436	83.716	58.239	120.471
	Proportion of systematic variation explained:	0.514	1.015	1.044	0.785

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Every year, hundreds of lives are lost in traffic accidents in Sweden. To prevent this, it is necessary to have a firm understanding of the relations that influence this.

The aim of this thesis is to investigate accidents between pedestrians and motorized vehicles, and between bicyclists and motorized vehicles. The focus is on (a) the relation between the number of road users and the number of accidents (safety performance functions) and the reliability of those models; and (b) the relation between speed environment, age of the victim and the injury severity/outcome.

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