CHALMERS
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The Effect of Advanced Automatic Collision Notification (AACN) on Road Fatality Reduction in Sweden

Master's thesis in Complex Adaptive Systems

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Abstract

Road traffic accidents account for approximately 1.3 million fatalities each year and are the eighth most common cause of death globally and the leading cause of death for people between the age of 15 and 29. The outcome of a collision is affected by actions taken before, during, and after the collision. By optimizing these actions fatalities and injuries in traffic can be reduced. In addition to injury reduction due to active and passive safety systems, emergency medical service providers play an important role for the medical outcome of the persons involved in a collision. Advanced Automatic Collision Notification (AACN) is a system that, given a collision, can establish a communication link with the rescue services and forward the collision location as well as an estimation of the injury severity of the occupants involved. An AACN system is thus able to provide information to aid pre-hospital triage and give the emergency service operator information that is vital when deciding on appropriate action. Using this information it is more likely that appropriate medical service units can be dispatched to the collision scene and that patients in need of trauma care can be identified at an early stage, possibly enabling swifter transport to a medical facility with adequate trauma care level.

To evaluate the potential benefit of AACN in Sweden a benefit analysis based on accidents during the years 2006 to 2014 was conducted. Two different databases were used: 1) the statistical database STRADA (Swedish Traffic Accident Data Acquisition) and 2) the in-depth database of fatal accidents in the Swedish road transport system. The two databases were matched to identify the cases relevant for the analysis. Variables assumed to affect the outcome were selected and included in a multivariable logistic regression model. Thereafter, backward selection with stepwise exclusion of variables with p-value > 0.1 was carried out to obtain the final model. In addition to exclusion based on significance, variables with an estimated effect that were not consistent with previous research were excluded. Using the final model an estimated fatality reduction due to AACN was obtained by calculating the probability to die without AACN (actual outcome) and compare it to the probability to die when using AACN (alternative outcome).

The variables 'admission to trauma center', 'age' and 'injury severity' were identified as significant. Based on regression coefficients the effect of trauma center admission was associated with an odds ratio of 0.781 (95% CI = 0.609-1.003), thus beneficial. With additional restrictions (distance and AACN performance) applied to cases with alternative outcome, AACN was estimated to reduce road fatalities by 8.6% (95% CI = -0.3-16.4%). To further improve the estimation model a better defined trauma classification is needed along with additional accident data, possibly obtained with a better match between STRADA and in-depth cases.

Keywords: Advanced Automatic Collision Notification, AACN, post-crash, injury prediction, fatality reduction, hospital classification, emergency medical service

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JONATHAN JONSSON

Contents

1 Introduction

Road traffic accidents account for approximately 1.3 million fatalities each year (WHO, 2013). Almost 50% of these fatalities occur among drivers and passengers of 4-wheeled vehicles. In the event of a collision, notification to the rescue services and pre-hospital triage are most likely to be performed by an occupant or bystander that has observed the collision. If no one has observed the collision and the occupants are unable to notify rescue services the notification time, i.e. the time between the collision and the notification to the rescue services, is extended which affect the chance of survival negatively (Wu et al., 2013; Clark et al., 2002). Advanced Automatic Collision Notification (AACN) is a system that, given a collision, can establish a communication link with the rescue services and forward the collision location, as well as the expected injury severity of the occupants involved. The injury severity estimation is based on collision parameters obtained from the vehicle's on-board sensors. Using the information provided by AACN it is more likely that appropriate medical service units can be dispatched to the crash scene and that injured occupants can be transported to hospitals with adequate trauma care level. MacKenzie et al. (2006) suggests that the in-hospital fatality risk is 20% lower when treating seriously injured patient at a trauma center (TC) compared to a non-trauma center (non-TC), which emphasizes the importance of pre-hospital triage and proper target hospital. AACN has potential to decrease the fatality risk of occupants involved in a collision, both by shorten the notification time (Ohlin et al., 2014; Wu et al., 2013) and by estimating injury severity (Schulman et al. 2010). To what extent the injury severity estimation can help reducing road fatalities is not determined and needs to be further investigated. This thesis aims at widening the understanding of how, and to what extent, AACN can reduce the number of road fatalities in Sweden.

1.1 Purpose

Because collision characteristics and rescue service operation differ from country to country the potential benefit of AACN is most likely country dependent. Since no study has investigated the potential benefit of AACN in Sweden this thesis aims at conducting such a study. The main purpose is to estimate the benefit of AACN in terms of how the fatality risk would be affected by implementation of such system.

1.2 Scope

The benefit estimation will be focused on the potential reduction in road fatalities and will not evaluate the system's potential to reduce injury severity. To determine injury reduction as a function of AACN was too complex and time consuming to fit the scope of this thesis.

1.3 Thesis outline

In the beginning of this thesis the reader is introduced to the current situation and existing post-crash systems and their functionality. The background section also addresses the parameters possibly affected by an AACN system. Thereafter, the methodology is described by first presenting a high-level description of the analysis and then explaining the different parts in detail. The main results along with a sensitivity analysis are presented short and concise whereas the following discussion contains elaborations and analyses of the results as well as methodology reflections.

2 Background

Fatalities in road transport systems are the eighth most common cause of death globally and the leading cause of death for young people between the age of 15 and 29 (WHO, 2013). The outcome of an accident is affected by actions taken before, during and after the collision and by optimizing these actions fatalities and disabilities in traffic can be reduced. Historically, the focus has been on improving passive safety systems to better protect the occupants in a collision. Today, major efforts are made to avoid collisions and mitigate its consequences using active safety and autonomous systems, such as autonomous emergency steering and autonomous emergency breaking. However, until flawless autonomous driving is introduced, if ever, car collisions will still occur and when they do emergency medical service (EMS) providers plays an important role for the medical outcome of the persons involved in a collision.

Today, the vast majority of the collisions are reported to rescue services by an occupant or a bystander (European Commission, 2013), thus information about the accident and the injury situation are provided by people at the crash scene, presumably without adequate medical knowledge. Based on this information the emergency service operator receiving the call must decide on appropriate action, such as whether or not to send a helicopter to the crash scene and how many ambulances that are needed. When arriving at the crash scene it's the EMS personnel's responsibility to evaluate the situation and decide on appropriate target medical facilities for the injured occupants. Determining the target hospital to which an injured patient is transported can have major impact on subsequent mortality (MacKenzie et al. 2006). Although emergency hospitals in general offer the same kind of basic emergency services there are certain trauma centers with additional equipment and expertise for treating severely injured patients. Throughout this chain of events several vital decisions are made and if the basis for decision can be improved there is much to gain.

In the event of a collision there are several parameters affecting the outcome. First of all, the time aspect plays an important role in minimizing fatality risk (Ohlin et al., 2014; Wu et al., 2013; Clark et al., 2002). There are a few key time measures than can be used to evaluate the time effectiveness of a rescue operation. These are 'notification time', defined as the time between the accident and the notification to rescue services, 'response time' which is the time it takes for EMS personnel to reach the accident scene, 'transportation time', defined as the time between leaving the scene and arriving at the hospital and 'rescue time', the over all time from accident to hospital arrival. Secondly, the means of transportation between the accident scene and the hospital can affect the outcome (German Trauma Society, 2015) as well as the rescue time. An ambulance helicopter has several advantages compared to ground ambulance and several studies suggests that the fatality risk is reduced when transporting severely injured patients by helicopter compared to ground ambulance (Desmettre et al. 2012; Abe et al. 2014; Andruszkow et al. 2014; German Trauma Society, 2015). Thirdly, which hospital the patient is taken to plays an important role for the outcome (MacKenzie et al. 2010; Hilbert et al. 2010). A system like AACN (Advanced Automatic Collision Notification) can affect all of these parameters associated with patient outcome in a collision whereas a system like AACNs predecessor ACN (Automatic Collision Notification) only affects some of them.

2.1 Automatic Collision Notification (ACN)

ACN is the predecessor to AACN and aims primarily at shorten the notification time. Given a collision, or if manually activated, ACN can notify the rescue services and establishing a communication link between the car and the emergency service operator as well as forwarding the position at where the collision took place. This enables a swift response from the rescue services even in situations when no one has observed the collision and the occupants are unable to contact rescue services themselves. By using the exact positioning provided by ACN the risk of inaccurate position information is minimized as well. ACN technology has been on the market for some time and are known for example as eCall (European Commission, 2015a). Despite this, the market penetration is still low (European Commission, 2013) but a recent regulation adopted by the European Parliament demanding all new cars in the EU to be equipped with ACN in April 2018 (European Commission, 2015b) will gradually increase the number of cars equipped.

Several studies (Ohlin et al., 2014; Wu et al., 2013; Lahausse et al., 2008; Clark et al., 2002) have concluded that by shorten the notification time to less than one minute the number of road fatalities can be reduced. The suggested reduction differs between the studies and ranges from 1.87% (Wu et al., 2013) to 11% (Lahausse et al., 2008). Ohlin et al. (2014) conducted a case-by-case study based on Swedish accident data from 2011 and suggested that ACN could have reduced the fatalities by 3.2%. In an impact assessment for eCall produced in 2011 for EU the fatality reduction due to ACN was estimated to be 1-10%, depending on country, and the reduction of severity of injuries was estimated to between 2 and 15% (European Commission, 2011). For Sweden, the reduction in traffic deaths was estimated to 2-4% and the estimation for injury severity reduction was 3-4%. Compared to the more advanced system AACN, ACN has limitations when it comes to aiding the emergency medical services to decide on appropriate action regarding rescue unit type and target hospital.

2.2 Advanced Automatic Collision Notification (AACN)

AACN is a system that exceeds ACN since it, in addition to ACN, also estimates the injury severity of the occupants involved in a collision. The injury estimation is based on data obtained from the vehicle's on-board sensors and is transmitted to the rescue service operator along with other vital information regarding the accident, such as accident location and number of passengers. An AACN system is able to provide information to aid pre-hospital triage and give the emergency service operator information about the expected injury severity, information that is vital when deciding on appropriate action. Using this information it is more likely that appropriate medical service units can be dispatched to the crash scene and that patients in need of trauma care can be identified at an early stage, possibly enabling swifter transport to a medical facility with adequate trauma level.

The injury severity estimation is based on an algorithm using a number of parameters obtained from the vehicle's on-board sensors, such as change in velocity, principal direction of force, seatbelt use, airbag deployment, multiple impacts etc. One well established algorithm is called "URGENCY" and was trained on US crash data to predict the risk of an occupant being seriously injured in the crash (Malliaris et al., 1997; Rauscher et al., 2009). Different car manufactures may use different algorithms and set of variables but the objective remains the same, to determine the probability of severely injured occupants. Several car manufactures offers AACN functionality in their vehicles, such as GM with their OnStar and BMW with their ConnectedDrive, but the overall market penetration is still very low (European Commission, 2013).

Schulman et al. (2010) evaluated the potential impact of AACN for the pre-hospital triage of occupants involved in crashes where no contact was established with the vehicle or when injuries were underestimated. The authors found that in 20% of the cases where no call was initially made the occupants needed hospital care and that these cases could be improved by faster triage. They also found that 13% of the occupants who felt they were uninjured actually required hospitalization, indicating that in some cases occupants cannot estimate their own injuries and that AACN can provide important triage decision-support.

2.3 Hospital trauma level

In many countries, e.g. US and Germany, hospitals are classified based on their ability to perform trauma care. A level 1 TC has the highest ability to treat trauma patients and provides the highest level of surgical care whereas a non-TC only provides basic emergency services. In a study by MacKenzie et al. (2006) the difference in mortality between level 1 TCs and non-TCs in the US were examined. The findings suggests that the in-hospital mortality rate and one-year mortality rate are 20% and 25% lower, respectively, at a level 1 TC compared to a non-TC. A German study by Hilbert et al. (2010) compares the mortality rate for severe injuries (AIS3+) at Germanys ten top-scoring TCs to the ten lowest-scoring TCs. The authors concluded that the fatality rate was almost twice as high (16.6% compared to 8.7%) at the ten lowest-scoring centers. The consequences of a road traffic collision are thus presumably partly depended on which hospital trauma patients are omitted to. Hence, AACN systems can provide vital information for the occupants involved in a road traffic collision.

2.4 Transport by helicopter

The main advantages of helicopter transport are easy to understand. A helicopter can travel much faster than an ambulance and can reach remote locations. These features enable a shorter rescue time and allow patients to be transported longer distances. If transport distance is extended, patients who normally would be transported to the nearest hospital can possible be transported directly to a TC, which can affect the chance of survival and eliminate the need for a potential secondary transport. Furthermore, a helicopter offers a smoother transport than a ground ambulance minimizing the risk of exacerbating the injuries due to a bumpy ride to the hospital. The benefit of helicopter transport compared to ground ambulance is however debated, but several recent studies (Desmettre et al. 2012; Abe et al. 2014; Andruszkow et al. 2014) based on data from different countries suggests that the fatality risk is reduced when transporting severely injured patient by helicopter. In the German guidelines on treatment of patients with severe and multiple injuries established by the German Trauma Society the advantages of helicopter transport are discussed as well. By reviewing several studies comparing fatality rate between helicopter and ground ambulance the German Trauma Society concludes that helicopter transport in general is associated with reduced fatality risk (German Trauma Society, 2015). The risk reduction differs between the studies and ranges from 8.2% to 52%.

2.5 Injury severity quantification

How injuries are classified is of great importance when deciding how and where to transport injured occupants. Today, Maximum Abbreviated Injury Score (MAIS) and Injury Severity Score (ISS) are commonly used when classifying injury severity. Abbreviated Injury Score (AIS) is an anatomical-based coding system describing the threat to life associated with the injury, ranging from 1 (Minor) to 6 (Maximum) (Association for the Advancement of Automotive Medicine, 2015). Each injury is coded with an AIS-value and MAIS is defined as the highest AIS-value, i.e. the worst injury sustained. ISS is based on the most severe injuries in the three most severely injured body regions, thus ISS describes multiple injuries better than MAIS. The AIS values for these injuries are squared and added together to get the corresponding ISS-value. ISS is ranging from 1 to 75 and the maximum value is obtained if there are three AIS5 injuries or if any of the injuries has an AIS value of 6 (Baker et al. 1974).

The use of AIS to classify injuries in AACN applications is debated and several authors suggests that there are more suitable ways of classify injuries in motor vehicle crashes that better capture the fatality risk associated with the injuries (Weaver et al., 2013; Schoell et al., 2015a; Schoell et al., 2015b). Weaver et al. (2013) suggest that classifying injuries using Mortality Risk Ratio (MRR) and/or MRR_{MAIS} instead of AIS would provide a better quantification of mortality associated with the injuries common in motor vehicle crashes. The authors suggest that AIS fails to capture the mortality associated with some of the most frequent injuries sustained in motor vehicle crashes. Another injury classification discussed in the context of AACN is Time Sensitivity Score (TSS), describing the urgency with which a specific injury requires treatment. Schoell et al. (2015b) suggests that TSS better capture the urgency to treat a specific injury than the AIS classification and that TSS could be useful in AACN systems for identifying highly time sensitive injuries requiring swift treatment at a trauma center.

2.6 Population density

Several studies (Clark, 2003; Clark et al., 2004; Goldstein et al., 2011; Travis et al., 2012) suggest that the mortality rate of severe injured is higher in rural areas than in urban areas. In rural areas the response time and transportation time are increased due to longer distances. One can also imagine that the probability for a crash to be unobserved is higher in rural areas compared to urban areas. All of these factors combined points towards the same conclusions drawn by the authors. Since Sweden is a country with low population density, the 4th lowest in Europe (Eurostat, 2013), one can argue that a system like AACN might have greater potential here than in smaller and more urban countries.

2.7 Allocation of resources

Besides the obvious aim to minimize under-triage, i.e. treating a seriously injured patient at a non-TC, the use of AACN can also improve the over-triaging. Treating minor injuries at a TC might overload these, potentially leading to a situation where seriously injured patient needs to be redirected to other hospital. Moreover, the allocation of resources can be optimized in a better way when patients are correctly triaged.

3 Method and material

The benefit analysis was based on accidents during the years 2006 to 2014. Two different databases were used: 1) the statistical database STRADA (Swedish Traffic Accident Data Acquisition) and 2) the in-depth database of fatal accidents in the Swedish road transport system. The two databases were matched to identify the cases relevant for the analyses. Variables assumed to affect the outcome were selected and included in the model. Thereafter, backward selection with stepwise exclusion of variables with *p-value* > *0.1* was carried out to obtain the final model. In addition to exclusion based on significance, variables with an estimated effect that were not consistent with previous research were excluded. Using the coefficient estimates in the final model the fatality probability was calculated for all fatalities in passenger cars, first by using the actual outcome parameters, obtained from STRADA, and then by changing the outcome parameters affected by AACN. The two probabilities were then compared to obtain an estimated fatality reduction due to AACN. In Figure 3.1 a high-level description of how the analysis was performed is presented.

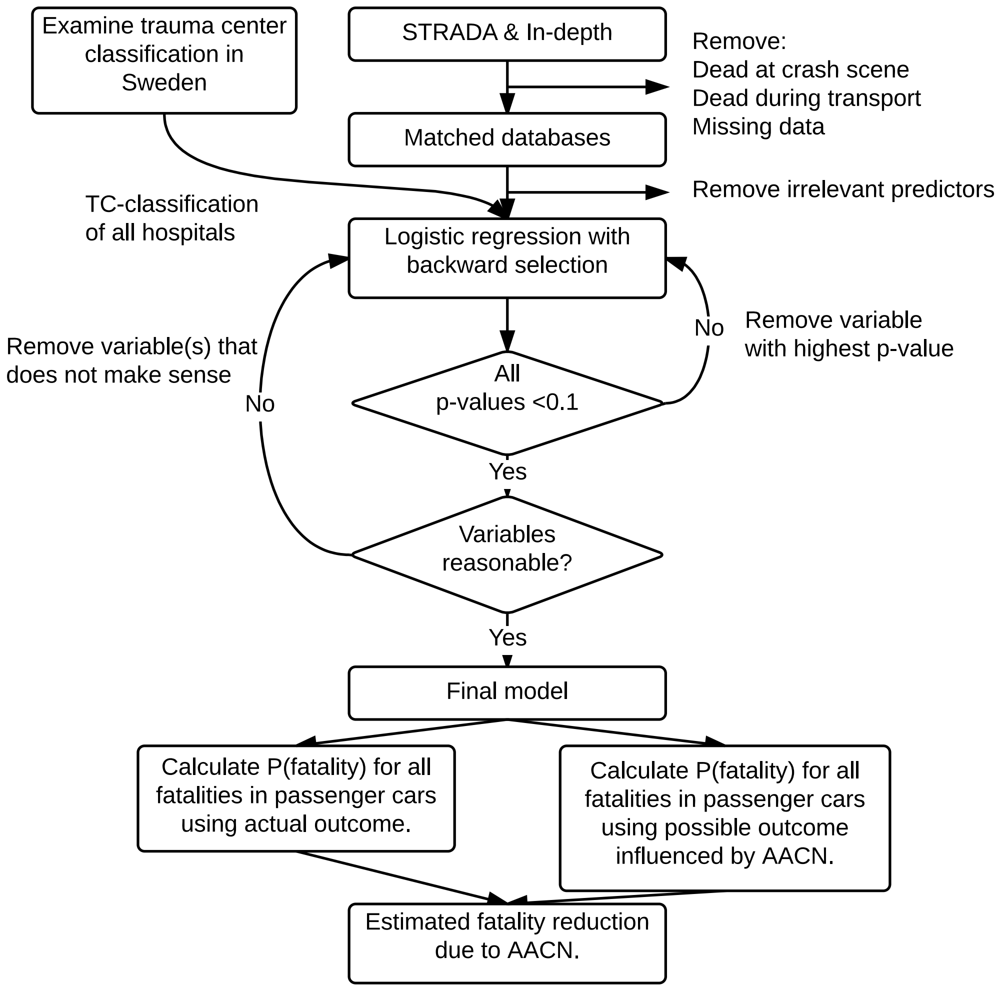

Figure 3.1: High-level description of how the analysis was performed.

3.1 Hospital classification

In Sweden there is no official trauma classification of hospitals and thus no obvious way to divide the hospitals into different trauma levels. Furthermore, there is no coherent system used to classify the resources available in each hospital, preventing a third party to quantitatively classify the hospitals according to other countries, e.g. US or German, trauma level standards. To qualitatively examine and classify each hospital is probably possible, but falls beyond the scope of this thesis. A trauma classification was however essential in order to include the effect of target hospital in the benefit estimation of AACN. Two different approaches were considered: Mortality rate per hospital and the use of University Hospitals as a proxy for trauma centers.

3.1.1 Mortality rate per hospital

A measure that can be used to characterize hospitals ability to treat trauma patients is 'mortality rate per hospital' which is a measure of how many percentages of the patients treated that died in the hospital. Provided that differences in injury severity and demography between patients are accounted for this measure provides a rating of mortality risk that can be compared between hospitals. However, due to the low number of in-hospital fatalities available for the analysis it was not possible to make a reasonable classification of hospitals based on mortality rate per hospital. The fact that only 10 of the 73 hospitals reporting to STRADA had 10 or more fatalities made it impossible to get statistic significant results of mortality rate per hospital, thus this measure was considered inappropriate to use for hospital classification.

3.1.2 University Hospitals

In Sweden there are seven so called 'University Hospitals' located in Stockholm (Solna), Gothenburg, Malmö/Lund, Uppsala, Linköping, Örebro and Umeå. These hospitals deliver more highly specialized health care than the other smaller hospitals, referred to as county hospitals. University Hospitals, except Örebro University Hospital, are the only hospitals in Sweden performing neurosurgery (Swedish Neurosurgical Society, 2015), which is sometimes essential in order to treat trauma to the brain or spinal cord. Due to the fact that University Hospitals possess the resources needed to treat major trauma it is plausible to classify the University Hospitals as TCs and the other hospitals as non-TCs. In the absence of an official trauma classification this classification was used in the study to determine if, and to what extent, treatment at a TC increases the chance of survival.

3.1.3 Trauma center coverage

One prerequisite for the classification of University Hospitals as trauma centers was that they could cover most of the accident locations, meaning that the distance between accident location and nearest trauma center was short enough so that the patients could have been transported to a TC within reasonable time, either by ground ambulance or helicopter. To determine whether or not the coverage of the University Hospitals were reasonable the distance between all fatal accident locations involving a passenger car and the nearest University Hospital was computed using GPS-coordinates. The distance was measured both as a straight line, representable when transporting by helicopter, and as actual road distance, representing transport distance by ground ambulance. The road distance was obtained from Google Maps using Google Distance Matrix API. The coverage by the University Hospitals was measured by looking at how many percentages of the accident locations that were covered at a certain distance from the nearest University Hospital. To have something to relate these findings to the coverage of nearest hospital and target hospital were calculated as well. Nearest hospital here means the hospital with the shortest air distance from the accident scene. Target hospital is the hospital to which the patient was taken according to STRADA records.

3.2 Description of the databases used

3.2.1 In-depth studies

The Swedish Transport Administration (STA) conducts detailed in-depth studies of every fatal traffic accident in Sweden with the aim to obtain a complete picture of what happened before, during and after the accident (Trafikverket, 2012). Crash investigators at STA systematically inspect the vehicles involved in fatal crashes and record the characteristics, such as direction of impact, vehicular intrusion, seat belt use, airbag deployment and tire properties. The crash site is also inspected to investigate road characteristics, collision objects, etc. Further information about injuries is provided from forensic examinations, questioning and witness statements from the police and reports from the emergency services. The in-depth database contains information about every person involved in the crash, regardless of whether the person died or not. Although this database is designed to perform case-by-case analysis the relevant parameter needed for this study, namely ‘location of death’, could be identified in the table-formatted data used. The in-depth data contained a text field with information about location of death but this field was not always filled in and sometimes hard to interpret. In the cases where location of death was missing the corresponding accident description was read and if the location of death could not be found there either it was coded as unknown. The location of death was divided into ‘accident scene’, ‘transport’, ‘hospital’ or ‘unknown’.

The in-depth studies contained 7 255 cases, of which 3 489 were fatalities. Since only deaths occurring after arriving to hospital were considered in this study all other cases were excluded. Cases where a person died of natural causes were excluded as well. This resulted in 943 cases remaining, of which 404 were travelling in a passenger car. In Figure 3.2 a flowchart is illustrating how the cases in the in-depth database and STRADA were selected and matched.

3.2.2 Swedish Traffic Accident Data Acquisition (STRADA)

STRADA is a Swedish national information system containing data of injuries and accidents in the entire road transport system (Transportstyrelsen, 2015). The database is based on information reported from both the police and the hospitals, providing a broad picture of the accident and the injuries sustained. Since 2003 all police districts are reporting to STRADA and the number of emergency hospitals reporting have been steadily increasing ever since. Today, all emergency hospitals are reporting to STRADA but during the years considered in this study, 2006 to 2014, the hospital

‘Akademiska Sjukhuset’ in Uppsala was not reporting to STRADA. Also, all hospitals reporting in the late 2014 were not reporting in the early 2006 since some hospitals started their reporting to STRADA during this period.

When extracting data from STRADA one need to specify the information wanted and from which data sources, i.e. police, hospital or both. Depending on how this request is designed the number of cases available may differ. For example, a request on individual level differs from one on injury level, and the number of cases obtained may differ if one wants both police and hospital reported data or if one of them is enough. The data used in this study was based on a request with police and hospital data combined and contained information at individual level.

During the years 2006-2014 there were 69 040 cases reported to STRADA containing both police and hospital data. Excluding cases with age less than 0 or larger than 100 resulted in 69 011 cases, of which 946 were coded as fatalities and the rest as non-fatal injured. Of the fatal injured, 463 were travelling in a passenger car and 483 were other road users. Fatalities from the in-depth studies (n=943) were matched with fatalities in STRADA using the accident unique STRADA-id. In accidents with multiple fatalities the parameters age, gender and occupant position were used to identify the correct match. Of those travelling in a passenger car 154 died in a hospital, according to in-depth database. The corresponding number for the other road users was 222, giving a total of 376 people deceased in hospital. The total number of cases in the matched dataset was thus 68 441. In Figure 3.2 a flowchart is illustrating how the cases in the STRADA database and in-depth were selected and matched.

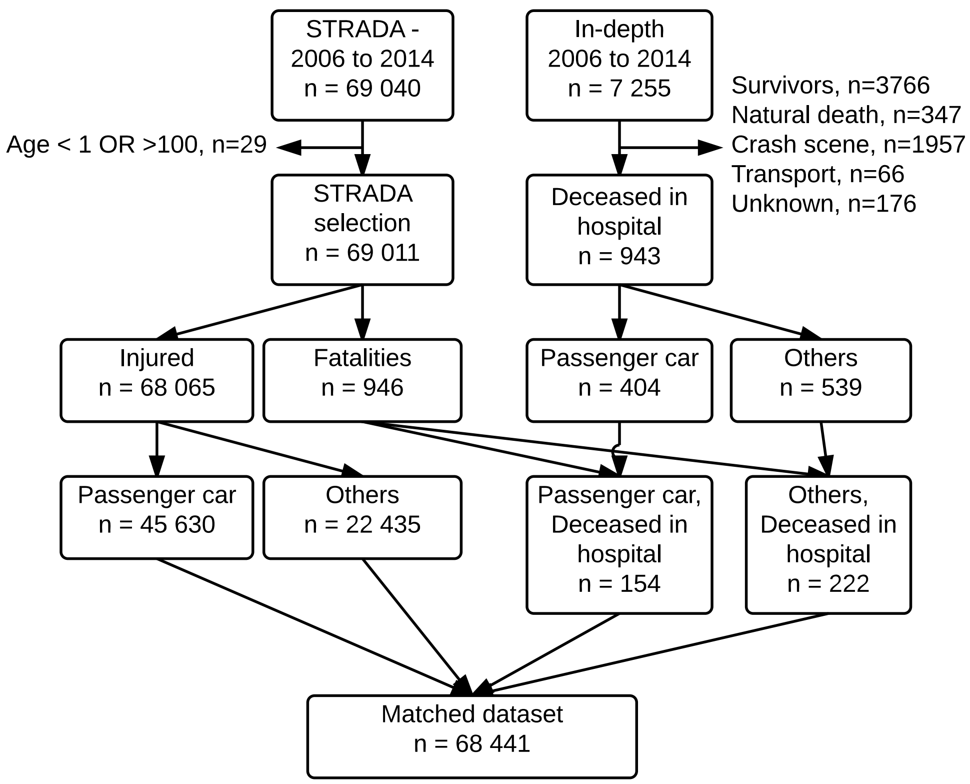

Figure 3.2: Flowchart illustrating how the cases in STRADA and in-depth were selected, excluded and matched.

3.2.3 Dataset characteristics

The patient characteristics in the matched dataset are presented in Table 3.1. When calculating ‘Rescue time’ the difference between police-reported ‘time of accident’ and hospital reported ‘time of hospital admission’ was used. However, due to poor reporting, mostly of ‘time of accident’, not all cases contained a proper ‘Rescue time’. In addition, if ‘Rescue time’ exceeded 720 minutes it was excluded and treated as a misreporting. The number of cases containing a proper rescue time was 64 124, of which 360 were fatalities. The reporting of means of transport was also incomplete. Only 55 256 cases, of which 367 were fatalities, were reported with either helicopter or ambulance transport.

Table 3.1: Characteristics of patients in the dataset used in the analysis

	Entire road transport system		Passenger cars only	
Variable	Dead, n=376	All, N=68 441	Dead, n=154	All, n=45 784
Dispatched to TC %	48,7	28,4	47,2	25,7
Transported by helicopter %	16,2	1,4	26,1	1,2
Distance to target hospital [km]	30,5	17,8	36,8	19,2
Age	52,1	37,2	45,1	37,5
Male %	67,5	56,7	69,7	54,0
Rescue time [min]	53,6	67,4	65,8	70,3
ISS	33,4	3,2	34,8	2,6

3.3 Model design

3.3.1 Multivariable regression analysis

To examine how the variables possibly influenced by AACN, e.g. target hospital and means of transportation, affects the fatality risk other variables not influenced by AACN, e.g. age and injury severity, must be accounted and adjusted for. To perform such analysis multivariable logistic regression with backward predictor selection was used. Multivariable logistic regression is a widely used method to relate one or several variables of interest to a binary outcome while accounting for confounding variables, which can be binary, numerical or categorical. The logistic regression was performed using the function ‘fitglm’ in MATLAB R2014b. The model used in the analysis was *logit*, defined as

$$\mathrm{logit(Y)} = \log\left(\frac{Y}{1-Y}\right) = Xb \qquad (3.1)$$

where Y is the fatality risk, X the input variables and b the coefficients calculated by the regression model. A similar approach, with backward stepwise logistic regression, was used by Alghnam et al. (2014) when they examined the in-hospital death among traffic crash victims in Saudi Arabia. The method worked well there and should thus be suitable in this project as well.

3.3.2 Outcome of interest

The outcome of interest in this analysis was whether or not a person involved in a traffic accident died as a result of the accident after arrival to hospital. All cases in the dataset where thus categorized as either dead or alive based on the information provided in STRADA hospital. Since exclusion of natural deaths had already been done in the in-depth database all cases coded as dead in STRADA were included.

3.3.3 Input variables

The database STRADA contains numerous of parameters without interest for this analysis thus all parameters included in STRADA were not considered but only variables assumed to influence the outcome. Moreover, parameters possibly affecting injury severity, such as belt use, helmet use, over speeding, drink-driving etc., were not included, only injury severity itself was considered. The variables included in the analysis are presented in Table 3.2. ISS was treated as categorical since the injury severity scale is not linear, i.e. the difference between 1 and 10 is not necessarily the same as the difference between 51 and 60.

Table 3.2 Variables included in the regression model

Variable	Type	Unit	Description
Dead	Binary	1=dead, 0=alive	Response variable
TC	Binary	1=yes, 0=no	If a patient was admitted to a trauma center or not
Helicopter	Binary	1=yes, 0=no	If a patient was transported by helicopter or not
Gender	Binary	1=female, 0=male	
Age	Continuous	[year]	
Distance	Continuous	[km]	Distance between accident location and target hospital
Rescue time	Continuous	[min]	Time from accident to hospital arrival
ISS	Categorical	1-3 as reference, 4-6, 7-9, …, 73-75	Injury severity

Backward selection was used to determine the final input variables. The procedure works as follows: Starting from a set of variables the one with the highest p-value is removed until all variable's p-values are below 0.1 (Vittinghoff et al. 2011). After removing a variable the regression model is recalculated using the variables left to obtain the new p-values. In addition to backward selection variables estimated to affect the fatality risk in an unreasonable way (based on previous research) were excluded from the model.

The effect of each independent variable in the final model was expressed as an odds ratio (OR). The OR for a variable x_n was calculated from equation (3.2) (Vittinghoff et al. 2011):

$$OR = \exp(\beta_n) \tag{3.2}$$

Where β_n is the coefficient estimate obtained from the regression model.

3.3.4 Statistical analysis

When developing the statistical model injured and fatalities from the entire road transport system were considered, i.e. the whole data set containing 68 441 cases. Using only passenger car related injuries and deaths did not provide enough data to get statistically significant results, possibly due to the low number of fatalities (n=154). Looking at characteristic differences between passenger car and the entire road transport system, presented in Table 3.1, it is reasonable to assume that using the entire road transport system in model development should not affect the outcome significantly. The biggest differences can be found among fatalities where those in passenger cars are transported by helicopter at a higher extent (26,1% vs. 16,2%), are younger (45,1 years vs. 52,1), have longer distance to target hospital (36,8 km vs. 30,5) and longer rescue time (65,8 min vs. 53,6).

3.3.5 Model performance

One common method used to validate predictive models is the split sampling approach where the dataset is split into training and validation set and the training set is used for fitting the model and validation is used to validate the performance of the fitted model. Since this method only uses part of the data for model development it does not make use of all the information contained in the dataset. Instead of the split sampling approach the model was validated using the area under the receiver operating characteristics curve (AUC), allowing the whole dataset to be used in model development. AUC is a measure of how well the model discriminate between the two outcomes. A value of 1 indicates perfect discrimination and a value of 0.5 implies that the model does not perform better than a guess.

3.4 Benefit estimation of AACN

With the statistical model the effect of AACN on road fatality reduction in Sweden was calculated based on fatalities in passenger cars. The number of road fatalities in passenger cars included in this analysis was 154. The effect was obtained by first calculating *P(fatality, no AACN)* for all cases using the actual outcome, i.e. using the parameter values obtained in STRADA and then calculating *P(fatality, AACN)* using an alternative outcome, i.e. changing the parameters affected by AACN. *P(fatality)* was obtained from:

$$P(fatality) = P(x_1, x_2, \dots, x_n) = \frac{\exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}{1 + \exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)} \tag{3.3}$$

Where x_n is the value of the variable and β_n the corresponding coefficient from the statistical model. *P(fatality, no AACN)* and *P(fatality, AACN)* were then averaged to get P_{NoAACN} and P_{AACN} which were used to calculated the effect of AACN. The effect was expressed both as odds ratio (OR), calculated from equation (3.4), and as relative risk (RR), from equation (3.5) (Vittinghoff et al. 2011). Using RR the change in fatality risk can be expressed in percentage by taking 1-RR. Thus, a value less than one implies a decrease in fatality risk and a value larger than one an increase.

$$OR = \exp\left(\log\left(\frac{P_{AACN}}{1 - P_{AACN}}\right) - \log\left(\frac{P_{NoAACN}}{1 - P_{NoAACN}}\right)\right) \tag{3.4}$$

$$RR = \frac{P_{AACN}}{P_{NoAACN}} \tag{3.5}$$

Confidence intervals (CI) for P_{NoAACN}, P_{AACN}, OR and RR were calculated using bootstrapping. The bootstrap procedure approximates sampling distribution of the statistics using a sampling procedure with replacement (Vittinghoff et al. 2011). First, cases were randomly selected from the original dataset (n=68 411 cases) using draw with replacement, i.e. the same sample can be drawn more than once. Then a logistic regression model was calculated as describes in Section 3.3. Using this model the parameters P_{NoAACN}, P_{AACN}, OR and RR were calculated as previously described. This procedure was repeated 10 000 times and the CIs were calculated as percentiles from the 10 000 values resampled for each parameter. The MATLAB function *bootstrp* was used.

3.4.1 Alternative outcome criteria

When considering the alternative outcome in the benefit estimation all cases where the target hospital could have been affected by AACN were revised. Fatalities that had sustained less severe injuries, defined as ISS < 9, would possible not have been identified by an AACN system and were thus not modified. Furthermore, the distance between accident location and nearest trauma center was sometimes too long, defined as > 150 km. These cases were not modified either, unless the distance to target hospital exceeded 150 km and the distance to nearest TC was shorter.

4 Results

4.1 Trauma center coverage

In Figure 4.1 the coverage of nearest hospital, target hospital and nearest TC are illustrated. Given that the mean rescue time for fatal accidents involving passenger cars in this study is approximately 66 minutes (Table 3.1) and that the ambulance helicopters operating in Sweden have a cruising speed of approximately 250 km/h (Scandinavian AirAmbulance, 2015) it is reasonable to assume a helicopter coverage of 125-150 km. The trauma centers could then cover around 85-88% of the accidents by helicopter. Thus it appears reasonable to assume that more than 85% of all patients involved in a motor vehicle crash could be transported to a TC if ambulance helicopter is used.

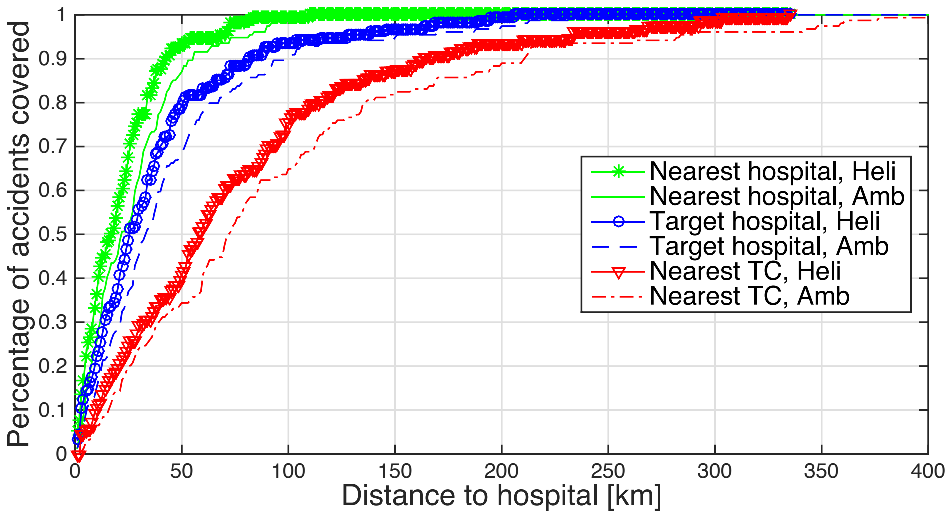

Figure 4.1: Hospital coverage measured as percentage of fatal accidents covered at a given distance from the nearest hospital (green), target hospital (blue) and nearest TC (red).

4.2 Statistical model

The backward selection procedure identified the variables ‘TC’, ‘Age’ and ‘ISS’ as significant. The variables ‘Helicopter’ and ‘Rescue time’ were excluded due to implausible parameter estimation. Helicopter transport was associated with a decrease in survival probability, but since the vast majority of studies regarding helicopter transport suggests an increase in survival probability with helicopter transport (Desmettre et al. 2012; Abe et al. 2014; Andruszkow et al. 2014; German Trauma Society, 2015) the variable was removed from the model. Also, longer rescue times were associated with higher survival probability. It was not possible to model quality and time spent for treatment at the accident location which could explain such effects, as extended treatment at the accident scene might be beneficial. Thus, ‘Rescue time’ was removed from the model as implausible.

In Table 4.1 the final logistic regression model with variables ‘TC’, ‘Age’ and ‘ISS’ is presented. Patients admitted to a trauma center instead of a non-trauma center were less likely to die (OR = 0.781, according to equation (3.2), 95% CI = 0.609-1.003). Older patients were more likely to die than younger patients (OR=1.030 per one year increase, 95% CI = 1.024-1.036). Finally, higher ISS value was associated with a higher risk of death (OR = 1.898 per three unit increase on average, 95% CI = 1.897-2.290).

The AUC for the final model was 0.9808 suggesting excellent discrimination and model performance.

Table 4.1: Model specifications for the final logit regression model with input variables 'TC', 'Age' and 'ISS', and response variable 'dead'.

Variable	Estimate	Standard error	P-value	Number of cases
Constant	-10.377	0.468	<0.001	68 411
TC	-0.247	0.128	0.053	68 411
Age	0.030	0.003	<0.001	68 411
ISS 1-3	Reference	Reference	Reference	50 911
ISS 4-6	1.574	0.606	0.009	10 166
ISS 7-9	3.683	0.528	<0.001	2 450
ISS 10-12	4.342	0.523	<0.001	1 450
ISS 13-15	4.955	0.503	<0.001	1 056
ISS 16-18	5.719	0.486	<0.001	784
ISS 19-21	6.284	0.509	<0.001	306
ISS 22-24	6.347	0.496	<0.001	365
ISS 25-27	7.060	0.491	<0.001	251
ISS 28-30	7.368	0.488	<0.001	217
ISS 31-33	7.916	0.541	<0.001	68
ISS 34-36	8.019	0.494	<0.001	142
ISS 37-39	8.978	0.524	<0.001	64
ISS 40-42	8.789	0.553	<0.001	46
ISS 43-45	9.039	0.529	<0.001	58
ISS 46-48	9.070	1.078	<0.001	5
ISS 49-51	9.296	0.557	<0.001	40
ISS 52-54	9.250	0.909	<0.001	7
ISS 55-57	9.041	0.802	<0.001	10
ISS 58-60	8.737	0.841	<0.001	9
ISS 64-66	9.583	1.126	<0.001	4
ISS 73-75	11.079	0.709	<0.001	32

4.3 The effect of AACN

The probability to die when not making use of AACN information was on average P_{NoAACN} = 0.151 (95% CI = 0.026-0.395) whereas the probability was P_{AACN} = 0.138 (95% CI = 0.023-0.366) on average when using AACN information to reroute seriously injured patients to a trauma center whenever possible. The corresponding odds ratio (equation (3.4)) was OR = 0.904 (95% CI = 0.816-1.004) and the relative risk (equation (3.5)) was RR = 0.914 (95% CI = 0.836-1.003). Thus AACN in Sweden was estimated to lead to a 8.6% fatality reduction (95% CI = -0.3-16.4%).

4.4 Sensitivity analysis

4.4.1 MAIS as injury classification

When using MAIS as injury classification instead of ISS the backward selection procedure identified the variables 'Distance', 'Age' and 'MAIS' as significant. 'Helicopter' and 'Rescue time' were excluded due to implausible parameter estimation. The model parameters are presented in Table 4.2. The AUC for this model was 0.9781 suggesting very good discrimination and model performance but not as good as the final model presented in Section 4.2. The fact that only 'Distance', 'Age' and 'MAIS' were significant when using 'MAIS' as injury classification makes this model useless to evaluate the benefit of AACN since none of these variables are directly affected by AACN.

Table 4.2. Model specifications for the logit regression model with input variables 'Distance, 'Age' and 'ISS', and response variable 'Dead'.

Variable	Estimate	SE	P-value	N cases
Constant	-10.351	0.466	<0.001	68 318
Distance	0.004	0.001	0.007	68 318
Age	0.026	0.003	<0.001	68 318
MAIS 1	Reference	Reference	Reference	50 843
MAIS 2	2.025	0.540	<0.001	11 898
MAIS 3	5.053	0.462	<0.001	4 176
MAIS 4	6.795	0.462	<0.001	892
MAIS 5	8.323	0.459	<0.001	478
MAIS 6	10.841	0.707	<0.001	31

4.4.2 The effect of different ISS-intervals

In the final model described in Section 4.2 the ISS-interval was set to three. Changing the interval affects the model coefficients and thus the estimated fatality reduction. In Figure 4.2 the change in coefficient estimation and p-value for the variable 'TC' (the variable affected most) are illustrated along with the estimated fatality reduction. The values are steady until the ISS-interval exceeds six after which fluctuations increases.

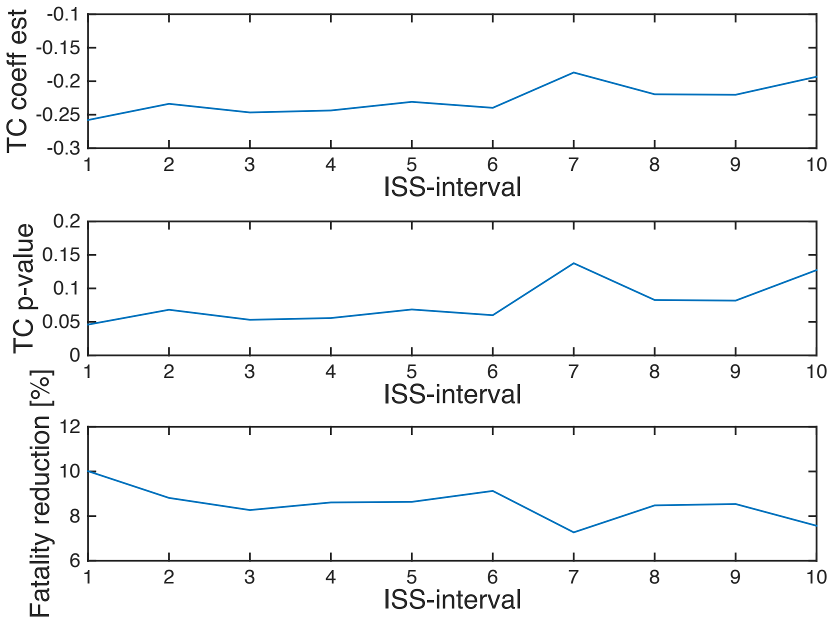

Figure 4.2: The effect of ISS-interval on coefficient estimation and p-value for the variable 'TC' and on the estimated fatality reduction.

4.4.3 Regression model using only passenger cars

When using only fatalities and injuries from passenger cars in the regression model the backward selection procedure identified the variables 'Age', 'Gender' and 'ISS' as significant. 'Helicopter' and 'Rescue time' were excluded due to implausible parameter estimation. The model parameters are presented in Table 4.3. The AUC for this model was 0.9788 suggesting very good discrimination and model performance but not as good as the final model presented in Section 4.2. The fact that only 'Age, 'Gender' and 'ISS' were significant makes this model useless to evaluate the benefit of AACN since none of these variables are affected by AACN.

Table 4.3. Model specifications with input variables 'Age', 'Gender' and 'ISS' when only fatalities and injuries from passenger cars were included in the analysis.

Variable	Estimate	SE	P-value	N cases
Constant	-9.732	0.537	<0.001	68 411
Age	0.019	0.005	<0.001	68 411
Gender	-0.398	0.207	0.055	68 411
ISS 1-3	Reference	Reference	Reference	50 911
…	…	…	…	…
ISS 73-75	11.414	1.161	<0.001	32

4.4.4 Örebro University Hospital as non-TC

Treating Örebro University Hospital, the only University Hospital without a neurosurgeon, as a non-TC did not change the variables included in the final model but affected the estimated effect of the variables slightly (Table 4.4). Based on this model the estimated fatality reduction was 7.9% (95% CI = -0.8-15.8%), thus a little lower than when Örebro University Hospital was treated as a TC.

Table 4.4. Model specifications with input variables 'Age', 'Gender' and 'ISS' when Örebro University Hospital is treated as non-TC.

Variable	Estimate	SE	P-value	N cases
Constant	-10.380	0.468	<0.001	68 411
TC	-0.236	0.128	0.064	68 411
Age	0.030	0.003	<0.001	68 411
ISS 1-3	Reference	Reference	Reference	50 911
…	…	…	…	…
ISS 73-75	11.077	0.709	<0.001	32

5 Discussion

5.1 Parameter estimation in final model

The final model estimated that the in-hospital fatality rate was lower at a TC compared to a non-TC, OR = 0.781 (95% CI = 0.609-1.003), after adjusting for age and injury severity (ISS). This finding is in line with the 20% estimated by MacKenzie et al. (2006) but lower than the suggested 91% by Hilbert et al. (2010). As in many other findings regarding health outcome, advanced age was associated with an increase in fatality risk, OR=1.030 per one year increase on average (95% CI = 1.024-1.036). Further, a three-unit increase in ISS-value was associated with a high increase in fatality, OR = 1.898 on average (95% CI = 1.897-2.290). A somewhat higher risk increase than the OR = 2.0 per five unit increase suggested by Alghnam et al. (2014).

5.2 Estimated fatality reduction

The study suggests that transporting seriously injured patients to a trauma center, whenever possible, is beneficial and can potentially reduce the number of road fatalities by 8.6%. However, the confidence interval ranges from -0.3 to 16.4% indicating a fairly large uncertainty in the estimation. Since no similar study, i.e. evaluating the possible effect of AACN in Sweden by a retrospective analysis, was found it is difficult to validate the suggested fatality reduction.

The fact that the benefit estimation is solely based on whether or not a patient is transported to a trauma center makes the result heavily depended on trauma center classification and assumptions regarding transport possibilities for injured occupants. For example, the difference in distance between target hospital and nearest TC is not taken into account, meaning that if target hospital is located 1 km from the accident scene it is still considered beneficial to transport the patient to a TC located 140 km away, which perhaps is no the case. Further, the benefit estimation assumes that it is always possible to transport a patient by helicopter between the accident scene and hospital if needed. This is probably not realistic though, since helicopters have other missions possibly preventing them to respond, also the weather does not always allow for helicopter use. Moreover, the fatality reduction only considers deaths at hospital, thus the model parameters might change if deaths at crash scene and during transport are included.

In the analysis it is assumed that an AACN system can always identify seriously injured (ISS≥9) occupants. A more realistic approach would have been to account for expected AACN performance. In a study by Buendia et al. (2015) based on Swedish accident data the authors suggest that injuries with ISS≥9 can be predicted with an AUC of 0.78. Including this in the analysis would thus decrease the expected fatality reduction. On the other hand, the study does not account for the benefit of reduced notification time. Something that could be beneficial also for people that died of natural causes, at crash scene or during transport. Also, fatality reduction is not the only benefit of AACN. An AACN system has potential to both reduce injury severity and length of stay in hospital, these advantages were not included in the study either.

5.3 Hospital classification

Since the emergency hospitals in Sweden are not classified according to a national trauma classification or similar the effect of trauma center admission are based on the classification made by the author. The use of University Hospitals as trauma centers can be questioned and does not necessary conform with a potential future trauma center classification. However, since no thorough investigation regarding trauma care at each emergency hospital was possible within the scope of this thesis the classification used was considered reasonable. In Sweden each county determines how the trauma care should be handled, thus there are no national coordination of trauma care (Regeringskansliet, 2015). The trauma care organization in Sweden is however under review by the Swedish national board of health and welfare and their findings will be presented in the summer of 2015 (Regeringskansliet, 2015). Hopefully this review can lead to a better trauma care coordination and eventually to a trauma center classification of the Swedish emergency hospitals.

The use of only two trauma center levels, i.e. TC or non-TC, is a limiting factor preventing the analysis to account for intermediate trauma level hospitals. It is plausible to assume that the hospitals can be divided into more than two trauma levels, as in Germany or the US, which possibly would affect the overall benefit of AACN. To further investigate the effect target hospital has on fatality risk a more thorough classification of the emergency hospitals, preferably including several trauma levels, is needed.

If the number of in-hospital fatalities had been more, the measure 'mortality rate per hospital' would probably be a good way to classify the emergency hospitals. The use of 'mortality rate per hospital' would also enable the possibility to divide hospitals into several trauma levels. However, the number of fatalities (n=376) included in this study was too few to get a relevant measure at all the hospitals.

The classification of Örebro University Hospital as TC can be debated. Since Örebro is a University Hospital, it appeared reasonable to include it as TC even though it lacks a neurosurgery (Swedish Neurosurgical Society, 2015). However, treating Örebro as non-TC did not change the outcome much (7.9% fatality reduction vs. 8.6%).

5.4 Trauma center coverage

TC coverage is an essential part to justify the use of University Hospitals as TCs. If the coverage is too low there will still be a lot of people that cannot be transported to a TC and thus not benefit from the initial assessment possible thanks to AACN. When examining the coverage of fatal accident locations only fatalities in passenger cars were included in the analysis. Including fatalities in the entire road transport system increased the coverage of TC since most of the fatal accidents involving pedestrians and cyclist occur in cities where the distance to nearest TC is often shorter. To only include fatalities in passenger cars seemed most reasonable since an AACN system currently only can affect the outcome of occupants travelling in a passenger car.

A reasonable flight distance for ambulance helicopters is hard to derive. Since no relevant literature was found regarding the subject an estimation was made based on mean rescue time for fatalities in passenger cars and the cruising speed of a typical ambulance helicopter used in Sweden. Whether or not this estimation is representable for real world cases can be discussed. For example, the mean flight distance between accident location involving passenger cars and target hospital was 47 km whereas the ten longest flight distances range from 190 km to 319 km. Also, the flight distance is dependent on where the helicopters are stationed and where they are located at the time of the alarm. The assumption that over 85% can be transported to a TC may not hold when taking these factors into account.

5.5 Databases

Two different data sources were used to identify the relevant cases, thus the matching process was of great importance for the subsequent analysis. Ideally, most fatalities in STRADA should match the in-depth cases coded as 'deceased in hospital' but that was not the case as only 376 of the 946 fatalities in STRADA did match. Partly, this is explained by the number of cases in the in-depth database coded as 'unknown location of death' (n=176). Also, fatalities coded as 'deceased during transport' (n=66) are presumably reported in STRADA since these most likely are transported to an emergency department. However, there are still very many cases left to explain. No thorough examination of the non-matching cases was performed and to further enlarge the dataset such examination is probably needed.

Only fatalities matching the in-depth were included in the matched dataset, but all non-fatal injured from STRADA were included. This could possibly be a cause for bias in the matched dataset. However, no other cause than pure chance is known for some fatalities in STRADA to be matched and some not, thus the matching itself was not considered a cause for bias.

When classifying the cases in in-depth database the notes from the investigators were sometimes hard to interpret, thus the location of death was not always clear. Only cases that clearly stated that a hospital was the location of death were coded as 'deceased in hospital'. Further, cases described as 'dead on arrival' or 'declared dead on arrival' etc. were not coded as 'deceased in hospital'. All these factors probably contribute to the low number of matches and presumably the cases identified as 'deceased in hospital' in the in-depth database are not all persons that actually died at a hospital. However, a strict inclusion criteria, like the one used, was considered the best way to separate between 'deceased in hospital' and 'others' given the data used.

5.6 ISS as injury classification

The only injury classifications available in STRADA were ISS and MAIS. ISS was considered to better capture polytrauma than MAIS, hence ISS was used in the final model. When comparing the model using MAIS to the one using ISS one finds that 'trauma center' was not included in the former, possibly indicating that MAIS does not capture the overall injury severity good enough to estimate the threat to life associated with the injuries sustained. Further, the use of AIS or MAIS to classify injuries in AACN applications are debated and several authors suggests that there are more suitable ways of classify injuries in motor vehicle crashes that better capture the fatality risk associated with the injuries, such as Mortality Risk Ratio or Time Sensitivity Score (Weaver et al., 2013; Schoell et al., 2015a; Schoell et al., 2015b). Since ISS is based on AIS it is reasonable to question the performance of ISS in AACN applications as well, but given the conditions for this study ISS was considered the better choice. However, to fully capture and estimate the injury severity of occupants involved in a motor vehicle accident it might be beneficial to establish new or updated ways to measure injury severity.

In the final model the estimated coefficient for ISS does not always increase with increased ISS-value as expected. For example the coefficient for ISS 40-42 is lower than the one for ISS 37-39 (8.789 vs. 8.978) and the same goes for ISS 55-57 compared to ISS 52-54 (9.041 vs. 9.250). However, looking at the overall trend there is a clear increase in ISS-coefficient with increased ISS-value. To illustrate this further the ISS-coefficient for three different ISS-intervals are plotted against the corresponding ISS-values in Figure 5.1. Except the decrease in ISS-coefficient around ISS 60 all three curves exhibit an overall positive trend, although fluctuations differs between the curves. The overall fluctuations are probably caused by the difference in the number of cases for each ISS-value (Table 4.1). Regarding the decrease around ISS 60 there are rather few cases available with ISS>50 (n=64), thus the fluctuations among theses values will have a large impact on the result, possibly explaining the decrease.

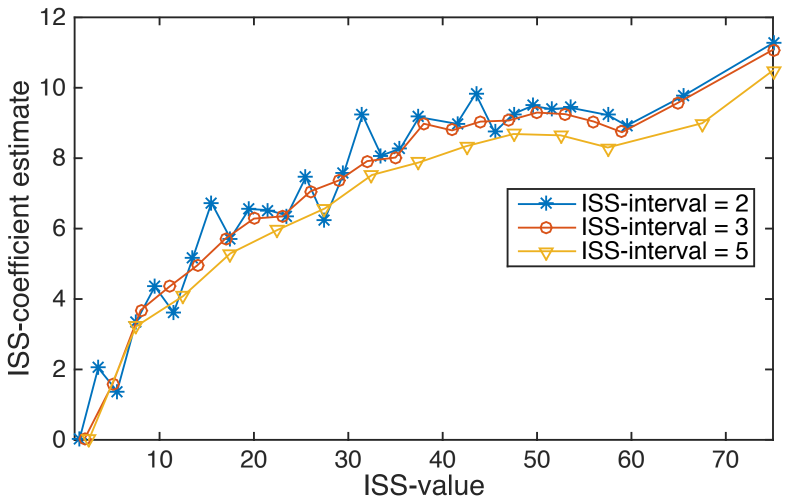

Figure 5.1: Variation of ISS-coefficient with different ISS-intervals.

As seen in Figure 4.2 different ISS-intervals give different parameter estimations and potential fatality reductions. In the final model an ISS-interval of three was used and whether or not this was the best parameter choice is difficult to say. Larger ISS-interval will cause information to be lost but too small interval will reduce case numbers per interval. In Figure 4.2 the fluctuations are rather small for ISS-interval less than seven but above that the fluctuations increases. An ISS-interval of three was thus considered suitable to group values together while still containing the information in the ISS-values.

5.7 Using only accidents involving passenger cars

To obtain as good picture as possible over how different variables affects the fatality risk a large dataset was essential. Including injuries and fatalities from the entire road transport system instead of only passenger cars increased the dataset from around 46 000 to over 68 000 but most importantly the number of fatalities increased from 154 to 376. It was assumed that independent of how the injures were sustained the medical outcome for persons with similar injuries and demography were the same when treated at the same hospital. However, it is plausible that injuries sustained in a passenger car is different from injures sustained on a motorcycle even though the ISS-values are the same. The benefit of a larger dataset was though considered more valuable than the potential drawback of including injuries from other than passenger cars.

When the regression model was based on injured and fatalities from passenger cars only none of the variables identified as significant ('Age', 'Gender' and 'ISS') are affected by AACN. Thus this model cannot be used to evaluate AACN benefit. The low number of fatalities in passenger cars (n=154) is probably one of the reasons for this. However, if the number of fatalities was higher a regression model based only on passenger cars would presumably be a better way to relate the fatality risk associated with injuries commonly occurring in car collisions.

5.8 Exclusion of 'Helicopter transport' and 'Rescue time'

Helicopter transport was associated with increased fatality risk, thus the opposite of what several recent studies (Desmettre et al. 2012; Abe et al. 2014; Andruszkow et al. 2014) and the German Trauma Society (2015) suggest. The fact that injured people transported by helicopter had more severe injuries than those transported by ground ambulance (mean ISS = 12.45 vs. 3.45) should not affect the estimation since injury severity is adjusted for in the model, unless the adjustment is flawed by ISS not being an accurate predictor of injury severity. Using the data available no obvious cause for this result was found.

Longer rescue times were associated with higher survival probability, thus not consistent with the assumption that swifter hospital care is beneficial. Rescue time was calculated from data relying on two different time reports (police and hospital). It is the author's impression that these times were not always reported correctly and accurately, which also Ohlin et al. (2014) mentioned in their study. Thus, the reliability in this variable can be questioned. It is plausible that a longer rescue time is beneficial if an extended on-scene medical treatment is of high quality and affects the survival probability positively, but since no information regarding on-scene medical treatment and the time spent on this was available for the analysis this effect could not be evaluated.

5.9 Future work

One of the key concepts of AACN is the possibility to better determine target hospital based on the injury estimation. To better estimate the effect of target hospital a more thorough trauma classification, preferably containing several trauma levels, would be advantageous. Also, the inclusion of additional data regarding pre-hospital treatment and injury classification would help to better estimate the effect of target hospital. Such data are however not available in STRADA, thus additional data sources would be needed to include these parameters in a future analysis.

The study would presumably benefit from the inclusion of more fatalities. The number of fatalities included (n=376) is rather low compared to the number of injured (n=68 065). If more fatalities can be included there is probably much to gain, not only for the analysis itself but it would also open up for a hospital classification based on mortality rate per hospital. Whether it is enough to improve the matching between STRADA and in-depth cases to obtain more fatalities or if additional data is required is difficult to tell at this point.

The benefit of AACN could be much more than deciding on target hospital. Using AACN the notification time and time to reach accident scene can be reduced, possibly affecting the outcome for persons that were not included in this study, i.e. persons that died of natural causes, at crash scene or during transport. Further, AACN has potential in decreasing the long-term injuries for people involved in a car collision, which is not included in this study either. To fully estimate all the benefits of AACN one need find a way to model all of these parameters along with how AACN can affect each of these. To do so, additional data would most likely be required.

6 Conclusions

This thesis is the first study evaluating the effect of the post crash system Advanced Automatic Collision Notification (AACN) on road fatality reduction in Sweden. Multivariable logistic regression with backwards selection was used to relate several input variables of interest to an output variable of interest. The variables identified as significant were ‘admission to trauma center’, ‘age’ and ‘injury severity (ISS)’. Based on this model it was suggested that transporting seriously injured patients to a trauma center, if possible, could potentially reduce the number of road fatalities by 8.6% (95% CI = -0.3-16.4%). Further research is required to better estimate the effect of AACN, not only on fatalities but also injuries. Moreover, additional studies on the input variables helicopter use and rescue time, currently giving implausible results, are needed as well as on further potentially relevant input variables. A larger dataset, or at least more fatalities, could enable a more accurate estimation.

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