# EVALUATING TRAFFIC SAFETY PERFORMANCE OF COUNTRIES USING DATA ENVELOPMENT ANALYSIS AND ACCIDENT PREDICTION MODELS

by


Adinda Van Espen

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# Abstract

Road safety is an issue of global importance, receiving both national and international attention. According to the World Health Organization, road traffic injuries are extrapolated to become the fifth leading cause of death in the world by 2030. Studies conducted to gain better insight into how countries can improve their road safety performance levels often use one single variable – the number of fatalities per million inhabitants – and focus predominantly on European countries. This thesis looks to develop and analyze models incorporating a wider range of countries as well as a wider range of road safety performance indicators using data envelopment analysis and accident prediction models. The first method, initially calculate the efficiency scores using three input variables (percentage of seatbelt use in front seat, road density, and total health expenditure as percentage of GDP) and two output variables (number of fatalities per million inhabitants and fatalities per million passenger cars). It was found that the addition of the percentage of seatbelt use in rear seats (fourth input variable) and the percentage of roads paved (fifth input variable) improved the efficiency scores and rankings. Overall, the percentage of seat belt use in front seats and the total health expenditure variables had the greatest importance. The second method developed three accident prediction models using the generalized linear modeling approach with the negative binomial error structure. The elasticity analysis revealed that, for Model 1 and Model 2, the health expenditure variable had the greatest impact on the number of fatalities. For Model 3, the seatbelt wearing rate in front seats and the seatbelt wearing rate in rear seats had the greatest effect on the number of fatalities.

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*To my family*

# 1. Introduction

## 1.1 Background

Road accidents are predicted to become the fifth leading cause of death in the world by 2030 if current trends continue. Worldwide, nearly 1.3 million people are killed annually from road traffic injuries. The UN General Assembly has therefore declared 2011-2020 as the Decade of Action for Road Safety wherein they will work to stabilize and reduce the forecasted level of road traffic deaths around the world (World Health Organization (WHO), 2012b).

Road accidents can cause considerable financial and human suffering as well as result in lost travel time and property damage. As road safety continues to receive increasing attention on both national and international levels, it becomes imperative that countries find better approaches to measure and monitor their road safety progress. Many countries currently only use the number of traffic fatalities per million inhabitants as a means of evaluating their road safety situation. Using more comprehensive data, such as road safety performance indicators, would allow for better insight and deeper understanding of the processes that lead to accidents (Shen et al., 2011).

Road safety performance indicators (RSPI) allow for monitoring of a country's progress as well as for international comparisons (Al Haji, 2005). The European Transport Safety Council (ETSC) defines an RSPI as "any measurement that is causally related to accidents or injuries, used in addition to a count of accidents or injuries, in order to indicate safety performance or understand the process that leads to accidents" (European Transport Safety Council, 2001, p. 5). These indicators can also be used for identifying trends, predicting problems, assessing policy impact, prioritizing measures, and benchmarking (Hermans, Van den Bossche, & Wets, 2008). Understanding the RSPIs can help explain additional factors that contribute to accidents, allow for the determination of risk factors, help identify corresponding interventions, and allow for monitoring the effectiveness of safety actions taken (Bao, Ruan, Shen, Hermans, & Janssens, 2012). RSPIs predominantly relate to the road user, the vehicle, and the road itself.

## 1.2 Problem Statement

Further development and improvement of the evaluation of the road safety performance of countries around the world has become an important issue. One way of doing so is by evaluating road safety performance indicators (RSPIs) in a more in-depth manner. This can be done by using a composite indicator methodology as has been previously done in other domains like economy, environment, and technology (Hermans, Brijs, Wets, & Vanhoof, 2009). The composite indicator methodology combines, integrates, and converts RSPI values into one single value, also called an efficiency score, to simplify the evaluation process. In the case of this thesis, this single value would allow for easier interpretation of a country's road safety performance. The methodology considers numerous weighting methods such as budget allocation, analytic hierarchy process, data envelopment analysis (DEA), factor analysis, and equal weighting (Nardo et al., 2005; Hermans et al., 2009). The efficiency scores can also be used for ranking of the countries. This type of ranking allows countries to assess their performance level and compare their performance level with that of another country. A benefit for doing so is that countries can use the scores and rankings to set targets and benchmarks which can help them improve their overall safety performance level. Another benefit of using the calculated efficiency scores for ranking compared to using the number of traffic fatalities per million inhabitants is that the latter does not indicate which aspect of road safety an inefficient country should focus on to improve its road safety level (Hermans et al., 2009).

Most previous work evaluates road traffic safety levels by developing accident prediction models using traditional or reactive methods for intersections or road sections (Sayed, Navin, & Abdelwahab, 1997; Sayed & Rodriguez, 1999). Although more recently, models are being developed using a more proactive approach and at a more aggregate zonal level, it was found that no study has been conducted to develop accident prediction models on an international level. Developing macroscopic level prediction models that help estimate the number of annual fatalities for a country rather than for a particular road network or intersection can provide national transportation agencies and governments with the tools to identify the main causes of fatalities in their country and to find ways to reduce this number by allowing them to identify the possible benefits of proposed remedial actions. For example, based on the model's predictions, a country's current situation leads to 1000 fatalities, however, by increasing the percentage of people wearing their seatbelt by 10%, they could reduce the number of fatalities by a certain percentage. Knowing this, a national transport agency or government may benefit from starting a national campaign to increase the number of people wearing their seatbelt by reminding them of the severe consequences it can have if not done so or by increasing or implementing a fine if caught not wearing a seatbelt (i.e., Click It or Ticket). Additionally, the elasticity analysis of a model assists in explaining how the outcome of each model is affected when the explanatory variables are changed using certain sensitivity. Doing so can allow countries to identify which RSPIs have a greater effect on the number of fatalities. If explanatory variable *A* has a greater elasticity value than explanatory variable *B*, a country may benefit more from improving variable *A* rather than variable *B* and they can try to put more focus on that particular RSPI.

## 1.3 Thesis Objectives

This thesis has several objectives. The main objective is to contribute to previous research efforts, which explore the ways of evaluating road safety performance of different countries using road safety performance indicators (RSPIs). This will be done by means of two different methods: the composite indicator methodology and the use of accident prediction models. The objective of the composite indicator methodology, in this thesis, is to combine, integrate, and convert the RSPI values into one single value using the data envelopment analysis method. This single value, called the efficiency score, will be used to evaluate and rank the countries safety performance. The evaluation and ranking will help them understand the magnitude of their problems as it allows for comparison with the other countries in the dataset. The objective of the second method is to develop accident prediction models using the generalized linear modeling approach with the negative binomial error structure to predict road traffic fatalities for a country rather than for a particular road network or intersection. The objective of the elasticity analysis of the accident prediction models is to provide countries with better insight into what RSPIs have the greatest effect on the number of road traffic fatalities and what RSPIs should be of interest to a government or transportation agency that is trying to reduce the number of fatalities in their respective country. For both methods, another significant objective is to expand previous research by increasing the number of countries that are being evaluated as well as the number of RSPIs being considered.

## 1.4 Thesis Structure

This thesis is organized into six chapters. Chapter 2 begins with the literature review. It discusses the various methods of evaluating road safety performance levels and explains the decision of this thesis to further explore this evaluation process using the composite indicator methodology and the development of accident prediction models – both on a macroscopic level.

Chapter 3 examines the composite indicator methodology using the data envelopment analysis (DEA) method as this method is the most comparable to the current most common evaluation method – the number of traffic fatalities per million inhabitants. With the use of the DEA method, an efficiency score is calculated for each country and the countries are ranked accordingly. This chapter includes two sets of analyses and uses data from the 178 WHO member countries. The number of countries for each analysis is dependent upon the available data. Analysis 1 evaluates the safety performance level of 36 countries using 3 and 4 input variables. Analysis 2, in turn, evaluates the safety performance level of 24 countries using 3, 4, and 5 input variables. Subsequently to the evaluation and the ranking of the countries’ safety performance levels, this chapter also examines whether adding additional input variables has any effect on the ranking.

Chapter 4 examines the development of accident prediction models on a macroscopic level using RSPIs. The models in this chapter also use data from the 178 WHO member countries. In total, three negative binomial regression models will be developed. Each model consists of an exposure variable and multiple explanatory variables (RSPIs). Model 1 is developed using data from 63 countries, Model 2 uses data from 50 countries, and Model 3 uses data from 48 countries. If a country does not have data for a particular RSPI, it will be eliminated from the analysis, hence the reduction in the final number of countries used to develop the models.

Chapter 5 will then look at a brief comparison between the two methods. Lastly, Chapter 6 presents the conclusions and future work. The appendices concluding the thesis consist of a sample DEA code and the definition of a fatality for each of the 178 WHO member countries. Both of the methods presented in this thesis use proactive approaches and road safety performance indicators to focus on identifying ways to reduce the number of fatalities. With the obtained results, strategies such as design, planning, education, policy/legislation, and enforcement can be developed to reduce accidents and accident severity.

# 2. Literature Review

## 2.1 Data Envelopment Analysis

### *2.1.1 Road Safety Performance Indicator Development and Selection Criteria*

Several researchers have discussed the development and the selection criteria for road safety performance indicators (RSPI) as this is an important process in the development of a composite road safety performance index (European Transport Safety Council (ETSC), 2001; Koornsta et al., 2002; European Commission, 2003; Al Haji, 2005; Vis, 2005; Hakkert & Gitelman (Eds.), 2007; Vis & Van Gent (Eds.), 2007; Wegman et al., 2008; European Commission, 2012).

The European Commission's *Road Safety Action Plan* (European Commission, 2003) specified the development of a European Road Safety Observatory (ERSO) which would focus primarily on road safety data and knowledge. From 2004-2008, the European Commission (2012) funded a project called SafetyNet, which targeted the development of this ERSO framework. Work Package 3 of this project dealt with the development of RSPIs and comprised of different deliverables. Deliverable 3.1 (Vis, 2005) is a state-of-the-art report on RSPIs and its main goal was to "develop a uniform methodology for measuring a coherent set of road safety performance indicators." In order to produce this report, questionnaires were sent to the 27 European countries to identify the availability and quality of road safety data that was available for those countries.

The SafetyNet report defined RSPIs as follows (Vis, 2005, p. 13):

> *"Safety Performance Indicators (SPI) are the measures (indicators), reflecting those operational conditions of the road safety traffic system, which influence the system's safety performance.*
>
> *The purpose of the SPI is:*
>
> - *to reflect the current safety conditions of a road traffic system (i.e., they are considered not necessarily in the context of a specific safety measure, but in the context of specific safety problems or safety gaps);*
> - *to measure the influence of various safety interventions, but not the stage or level of application of particular measures;*
> - *to compare between different road traffic systems (e.g. countries, regions, etc.)."*

The report investigates RSPIs in seven different road safety domains: alcohol and drugs use, speeds, protective systems, daytime running lights, vehicles, roads, and trauma management. These seven domains were established in an earlier report published by the ETSC (2001) called Transport Safety Performance Indicators and they reflect the different levels of the road safety system – the road user, the vehicle, and the road itself.

Following the definition presented above, the RSPIs for each road safety risk domains must "reflect the factors contributing to road accidents/injuries and characterize the scope of the problem identified" (Bao, 2010). The first domain deals with the use of alcohol and drugs. Although there is more awareness on the risk of getting in an accident under the influence of alcohol compared to the risk of getting in an accident under the influence of drugs, it can be expected that driving under the influence of drugs would imply a higher risk (Bao, 2010). A study done by Assum et al. (as stated by Bao, 2010, pg. 27) confirmed this expectation. The second domain has to do with speed. Speed plays a role in all accidents and excessive speed is one of the leading causes of accidents around the world (WHO, 2004). The third domain involves protective systems used by road users. Once an accident has occurred, protective systems such as seat belts, airbags, child restraint systems and helmets play a role in the severity of the injuries sustained (ETSC, 2001; Bao, 2010). Visibility is the fourth risk domain. Improved visibility such as the use of daytime running lights has a potential relevant effect on the severity of an accident (ETSC, 2011). The fifth domain relates to the vehicle itself. Many countries require regular vehicle inspections and have national standards for their vehicles. Vehicles that comply with the standards, such as working seat belts and airbag, would theoretically better protect the occupant in the event of an accident. Newer vehicles would have additional and newer safety features compared to older vehicles such as anti-lock braking systems and traction control which would help the driver in possibly avoiding an accident (Bao, 2010). The infrastructure and design of roads are part of the sixth domain (roads) as the probability of an accident is greatly influenced by the road network (ETSC, 2001). Based on the road design, a road user should clearly be able to recognize the function of the road and clarify their expected behaviour. The last domain belongs to trauma management. Post-accident medical treatment plays a vital role in the accident severity as the chance of survival and a better quality of life post-accident would be greatly enhanced with better medical care (ETSC, 2001). According to WHO (2004), many road accident fatalities could be prevented by more immediate and better medical care.

Deliverable 3.7a (Vis & Van Gent, 2007) is a report that presented a country comparison of the road safety performance of the 27 countries using developed RSPIs in the seven domains. The following list is a brief summary of some of the RSPIs that were developed in the seven risk domains and used for comparison in the SafetyNet report (Vis & Van Gent, 2007, p. 8-9):

1. **Alcohol and Drug Use**
   - Percentage of fatalities resulting from accidents involving at least one driver impaired by alcohol
   - Percentage of fatalities resulting from accidents involving at least one driver impaired by drugs other than alcohol
2. **Speeds**
   - Average speed (during daytime or the night)
   - Percentage of speed limit offenders
3. **Protective Systems**
   - Daytime wearing rates of seatbelts
   - Daytime wearing rates of safety helmets
4. **Visibility (Daytime Running Lights)**
   - Total usage rate of daytime running lights
5. **Vehicles**
   - Crashworthiness and vehicle age of the passenger car fleet
   - Vehicle fleet composition
6. **Roads**
   - Intersection types
   - Intersection density
7. **Trauma Management**
   - Number of EMS stations per 10,000 citizens
   - Availability and composition of EMS medical staff
   - Percentage of physicians and paramedics out of the total number of EMS staff
   - Number of EMS staff per 10,000 citizens
   - Demand for EMS response time (min)
   - Availability of trauma beds in permanent medical facilities
   - Total number of trauma care beds per 10,000 citizens

Deliverable 3.8 (Hakkert & Gitelman, 2007) is a road safety performance indicators manual that was developed to assist the European countries in the data collection process for the developed RSPIs as well as for making them comparable on a European level. The SafetyNet report (Vis, 2005) agreed upon the fact that the seven aforementioned road safety domains were the most important road safety risk areas but did state that the visibility domain (day time running lights) was considered an extra risk domain (Vis, 2005). Bao (2010) found through literature review that the effects of daytime running lights were unclear and considered the least important risk. This explains why Hermans et al. (2009), Bao (2010), & Bao et al. (2012) only used RSPIs that belonged to one of six road safety risk domains. For this reason, this thesis has used indicators which belong to these six domains. The use of which RSPIs have been used in previous literature will be discussed later.

### *2.1.2 Composite Road Safety Performance Index Development*

Once the RSPIs are selected, one can continue with the development of a composite road safety performance index. This type of index, like the Human Development Index, combines, integrates, and converts the RSPIs into a single value to allow for easier interpretation and comparison. The development of the composite road safety performance index was initiated by the desire to create benchmarks of national performances and rank a country's performance level on a global scale as well as over time (Al Haji, 2005).

Al Haji (2005) was probably the first researcher to develop an index that dealt with road safety issues and considered multiple indicators. In particular, he looked at the road safety levels of ten Asian countries as well as Sweden. He discussed many macroscopic models that could be used to describe the development of road safety nationally and internationally but many of those models only considered a few indicators. A hierarchical development of data was constructed to explain the macro-performance indicators layer using eight components (traffic risk, personal risk, vehicle safety, road situation, road user behaviour, socio-economic background, road safety organization, and enforcement). He generated a comprehensive list of 46 macro-indicators belonging to the eight domains. However, he only used 11 of the 46 indicators in the construction of his index as he stated that using all 46 of the indicators would take too much time to interpret and analyze and some of them needed further development and lacked in availability and acceptable quality. These 11 indicators had high data availability and had acceptable quality. He obtained data from various sources such as the World Data Bank, United Nations agencies, the World Health Organization (WHO), and the International Road Federation (IRF). The choice of which variable weights to use is a crucial one and the analysis considered four methods: two objective weighting methods (simple equal average and principal components analysis) and two subjective methods (assessment techniques from expert's opinion and assessment technique from literature and theory review). The road safety performance index was calculated using those four weighting methods, not to decide as to which approach is better but rather as to provide a comparison between them. With each technique, the countries were ranked according to their index score and classified into three groups (high, medium, and low road safety development). This rank showed how much improvement was required for each country to provide safer roads. All four approaches showed acceptable results and through a simple comparison, it was shown that even though the index scores varied somewhat between the different techniques, the rank remained the same.

During the course of the SafetyNet project, it was decided to incorporate the SUNflower approach, developed by Koornsta et al. (2002), to create an expansion report called SUNflowerNext (Wegman et al., 2008). SUNflowerNext aimed to "develop a knowledge-based framework for comprehensive benchmarking of road safety performances and developments of a country or of sub-national jurisdictions" by constructing a composite road safety performance index. They distinguished three main types of indicators: road safety performance indicators, implementation performance indicators, and policy performance indicators. In the end, they did not use any implementation performance indicators as no sound variables had been developed. In the end, they added another group of indicators called structure and culture to present some background variables for each country. Sticking to the seven domains established in the ETSC's report (2001) and the three groups of indicators mentioned above, 21 basic indicators were defined. Five trials were performed to develop the index using two weighting methods: the principal component analysis and the common factor analysis. The analysis was carried out on the same 27 European countries for which data had already been collected in the SafetyNet report. The calculated index score enabled the researchers to rank the countries and group them based on their safety performance (high, relatively high, medium, relatively low, low).

Building on previous work, researchers continued to investigate how to develop a composite road safety performance index and specifically which weighting method to use (Hermans, Van den Bossche, & Wets, 2008; Hermans, Brijs, Wets, & Vanhoof, 2009; Shen et al., 2009; Shen et al., 2011; Shen, Hermans, Brijs, Wets, & Vanhoof, 2012).

Since no prior agreement had been reached as to which weighting method was preferred for the construction of a composite road safety performance index, Hermans et al. (2008) focused mainly on the vital step of assigning weights to the individual indicators. Keeping in mind the weighting methods used by Al Haji (2005), the following five weighting methods were investigated: factor analysis, analytic hierarchy process, budget allocation, data envelopment analysis (DEA), and equal weighting. They used the seven domains established in Transport Safety Performance Indicators (ETSC, 2001) and selected one indicator to represent each domain. The road safety performance index was constructed using data for 21 European countries. The data was obtained from several different sources such as the International Road Traffic Accident Database (IRTAD), Eurostat, the WHO, and the Social Attitudes to Road Traffic Risk in Europe (SARTRE) project. Using the five different weighting methods, an index score was calculated for each country. Based on these scores, the countries were ranked from highest the lowest, where a higher score signified a higher ranking and a safer country in terms of road safety. The researchers were able to show that the DEA weighting method resulted in the highest correlation with the current method of road safety performance evaluation – the number of fatalities per million inhabitants.

Based on the conclusion reached by Hermans et al. (2008), the research by Hermans et al. (2009), Shen et al. (2009), Shen et al. (2011), and Shen et al. (2012) continued with the development of a composite road safety performance index using only the DEA weighting method. The DEA weighting method is a performance measurement technique that was developed by Charnes, Cooper, & Rhodes (1978) to evaluate the relative efficiency of a decision-making unit (DMU) based on the ratio of the weighted sum of outputs to the weighted sum of inputs. The method assigns weights to each DMU that ensure a maximized efficiency for that particular DMU. This method is different from the others in that the weights for each DMU (or country, in the case of this research) are not distributed evenly amongst the variables and do not add up to one. The precise methodology will be further explained in the following chapter.

Hermans et al. (2009) aimed at benchmarking road safety performances for 21 European countries by developing a data envelopment analysis road safety (DEA-RS) model. The DEA-RS model is different from the traditional DEA method in that it tries to minimize the efficiency score rather than maximize it. Compared to an economic field, road safety wants to maximize its inputs (i.e., seat belt use in front seats) and minimize its outputs (i.e., number of fatalities). To develop the DEA-RS model, they used indicators belonging to six of the previously mentioned seven domains, excluding the daytime running lights, as inputs and two road safety outcome variables as outputs. Based on the efficiency scores calculated for each of the 21 countries, the countries were ranked. The efficiency scores were then used to establish realistic benchmarks and targets. Shen et al. (2009) developed a multi-layer data envelopment analysis

(MLDEA) model which combined 21 indicators, with data of 26 European countries. They used the hierarchical structure of road safety performance indicators presented in the SUNflowerNext project (Wegman et al., 2008) to define and develop their road safety index. The use of the hierarchical structure is the main difference between a basic DEA model and an MLDEA model as well as the fact that the allocated weights for each layer of the hierarchy provide information on the relative importance of the corresponding indicator. The four types of indicators defined in that project are: final outcome indicators, safety performance indicators, policy performance indicators, and structure and culture indicators. For each of the four indicators, they introduced a set of sub-indicators that also followed a hierarchical structure – finally resulting in a total of 21 indicators. The DEA approach was then used to develop the MLDEA model as this approach uses country specific characteristics. Once the optimal overall index score for each country was calculated, the countries were ranked accordingly. Shen et al. (2011) further investigated the development of the generalized MLDEA model. They conducted a case study with their proposed MLDEA model to demonstrate how it is used to evaluate road safety performance. They used 13 hierarchical safety performance indicators for a set of 19 European countries. They started by calculating the index scores using the basic DEA model and then moved on to evaluating the scores using the MLDEA model. These two values were then compared to see whether a hierarchical structure improves the evaluation results. The results did indeed indicate the effectiveness of the multi-layer DEA model proposed in their study.

Shen et al. (2012) continued with the development of composing a road safety performance index by using three extensions of the traditional DEA model – the DEA-RS model (Hermans et al., 2009), the cross-efficiency model, and the categorical DEA model. They evaluated the road safety risk and identified useful benchmarks of 27 European countries based on. Three measures of risk exposure as input variables and one output variable were used to conduct the analysis. Countries were once again ranked according to their efficiency score, but this time, clustering analysis was applied to group countries with similar practices together – the third extension. In total, five cluster groups were classified. Each cluster was evaluated separately, meaning a country was only compared to countries within their cluster. This was done because some countries have different road safety evaluation methods and if not clustered, this could result in unrealistic benchmarks and targets for some. They argued that a developing country should not be compared with a highly developed country, as their resources for conducting research and obtaining data are not likely to be the same. As a result, the clustering allows for more reasonable and attainable target setting.

Bao (2010) took on a slightly different approach and tried to combine different sets of road safety performance indicators into an overall road safety performance index by studying multi-criteria decision making (MCDM) techniques. He focused mainly on the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for the creation of this index. The classical TOPSIS method, the fuzzy TOPSIS method, and the hierarchical fuzzy TOPSIS method were all MCDM techniques explored to derive composite index scores. Using six risk domains (alcohol and drugs, speed, protective systems, vehicle, roads, trauma management), Bao developed a set of 11 indicators for 21 European countries for which data was obtained from SATRE, ETSC, SafetyNet, United Nations Economic Commission for Europe (UNECE), European Commission (EC), Eurostat, and the WHO. Once the index scores were calculated, the countries were ranked correspondingly. It was determined that the hierarchical fuzzy TOPSIS method had a higher correlation with the number of fatalities per million inhabitants than the other two methods did. Bao et al. (2012) went on to expand on the previous work done by Bao (2010) by using an improved hierarchical fuzzy TOPSIS model, along with incorporating experts' knowledge, to create the composite index. They used MCDM methods to aggregate the indicators and the hierarchical fuzzy TOPSIS model reflected the hierarchical structure of the criteria. The index was created using the hierarchical structure consisting of the same six layers as in Bao (2010) with a total of 11 RSPIs for the 21 European countries. Road safety experts assigned the weight scores and the steps to calculate the final composite index scores were carried out. The countries were ranked based on their final scores. The improved hierarchical fuzzy TOPSIS model proved to be a valuable and effective in the evaluation of road safety. As these studies are quite recent, no additional research has been found to further support this work.

Although the literature review revealed that the composite road safety performance index rankings did not always match the traditional ranking of countries based on fatality rates, it was shown that the results improved when additional information was added – the use of multiple indicators. The studies showed that a composite road safety performance index gives a more enriched picture of a country's safety performance and can be a very meaningful tool. More recent research indicated that the DEA weighting method had the highest correlation compared current evaluation methods. Valuable recommendations for road safety can be made by policymakers by identifying the efficiency of current operations and suggesting targets for improvement. The use of benchmarks allows countries to gain insight into where they can improve their performance level and where the priorities lie. The comparison of the index values of a specific country over time can also provide very useful information as it would indicate the progress that country had made towards achieving the maximum level of road safety performance.

### *2.1.3 RSPIs Used in Previous Literature*

This section gives a brief overview of what RSPIs have been used in previous literature. It will provide the basis for the RSPIs selected for analysis in this thesis.

The composite road safety performance index developed by Al Haji (2005) was created using 11 of 46 indicators generated. He only used indicators belonging to the following six (of the eight) component groups: traffic risk, personal risk, vehicle safety, road situation, road user behaviour, and socio-economic background. Due to a lack of available data, he did not use any indicators in the road safety organization and enforcement domains. The socio-economic group was sub-divided into the following categories: urban population, income level, health level, and education level. The selected indicators make valuable contributions to the area of road safety development and included factors for the entire road traffic system: the road user, the vehicle, and the road itself. Table 1 (© Al Haji, 2005, reproduced with permission) lists the selected indicators.

**Table 1 – List of selected indicators used by Al Haji (2005)**

| **Indicator Type** | **Indicator** |
|---|---|
| Traffic risk | 1. Fatalities per 10,000 vehicles |
| Personal risk | 2. Fatalities per 100,000 people |
| Vehicle safety | 3. Percentage of vehicles not motorcyclists |
| Road situation | 4. Percentage of roads paved |
| Road user behaviour | 5. Percentage of front-seat belt use<br>6. Percentage of crash helmet use |
| Socio-economic background | **Urban population**<br>7. Percentage of urban population<br>**Income level**<br>8. Gross domestic product per capita<br>**Health level**<br>9. Life expectancy (years)<br>10. Severity index (% of number of fatalities per total casualties)<br>**Education level**<br>11. Adult literacy rates (% of persons over 15 years able to read and write) |

In the SUNflowerNext report, Wegman et al. (2008) used 21 basic indicators which belonged to the following three indicator groups: policy performance indicators, road safety performance indicators, and the structure and culture group. The road safety performance indicator group was sub-divided into final outcomes and intermediate outcomes. Shen et al. (2009) used the same 21 indicators as the SUNflowerNext project only they developed a hierarchical structure of these road safety performance indicators. Adapted from Wegman et al. (2008) and Shen et al. (2009), Table 2 is a brief summary of the basic indicators considered by these researchers.

**Table 2 – List of basic indicators used by Wegman et al. (2008) and Shen et al. (2009)**

| **Indicator Type** | **Indicators** |
|---|---|
| Policy performance indicators | 1. Safety targets<br>2. Selection of interventions<br>3. Economic evaluation<br>4. Monitoring<br>5. Stakeholders |
| Road safety performance indicators | **Final outcomes:**<br>6. Fatalities per million inhabitants<br>7. Fatalities per million passenger cars<br>8. Fatalities per 10 billion passenger-km travelled<br>9. Injury accidents per fatality<br>10. Share of pedestrian fatalities out of the total fatalities<br>11. Share of bicyclist fatalities out of the total fatalities<br>12. Share of motorcyclist fatalities out of the total fatalities<br>**Intermediate outcomes:**<br>13. Share of total for fatalities in drink-driving accidents<br>14. Daytime wearing rates of seatbelts in the front seats<br>15. Daytime wearing rates of seatbelts in the rear seats<br>16. Average EuroNCAP score of passenger car fleet<br>17. Median age of the passenger car fleet<br>18. Share of motorcycles in the vehicle fleet<br>19. Share of heavy goods vehicles (HGV) in the vehicle fleet |
| Structure and Culture | 20. Number of passenger cars per 1000 inhabitants<br>21. Population per 1 $km^2$ of country's territory |

With the continued development of the DEA method, Hermans et al. (2008) and Hermans et al. (2009) assumed that each road safety risk domain could be fully represented by selecting one indicator per domain which based on the best available indicator for each domain. Consequently, they selected the same indicators except for one. The main difference between the two studies is that Hermans et al. (2009) did not consider an indicator in the visibility risk domain (day time running lights). The paper does not indicate why they did not take this variable into consideration. Table 3 lists the indicators that were used to develop their DEA models. Hermans et al. (2009) used the following two road safety outcome variables as their output: number of road fatalities per million inhabitants and number of injury crashes per 100,000 inhabitants.

**Table 3 – List of indicators used by Hermans et al. (2008) and Hermans et al. (2009)**

| Risk Domain | Indicator |
|---|---|
| Alcohol and drugs | 1. Percentage of road users < BAC limit |
| Speed | 2. Percentage of drivers < speed limit |
| Protective Systems | 3. Seatbelt wearing rate in front |
| Visibility | 4. Day time running lights law* |
| Vehicle | 5. Percentage of cars < 6 years |
| Infrastructure | 6. Network density |
| Trauma Management | 7. Health expenditure as a GDP % |

** only considered by Hermans et al. (2008)*

Although Bao (2010) and Bao et al. (2012) used a different approach, they also considered 11 indicators all of which belonged to one of six road safety risk domains. Like Hermans et al. (2009), they also excluded the visibility domain, and in particular the daytime running lights indicator, as Bao (2010) found through literature review that the effects of daytime running lights were unclear and considered the least important risk. Table 4 lists the indicators used by Bao (2010) and Bao et al. (2012) (© Bao, Q., 2010, Master Thesis & © 2012, Elsevier, adapted with permission).

**Table 4 – List of indicators used by Bao (2010) and Bao et al. (2012)**

| Risk Domain | Indicator |
|---|---|
| Alcohol and drugs | 1. Percentage of surveyed drivers disrespecting the alcohol limit |
| Speed | 2. Percentage of surveyed drivers exceeding the speed limit in built-up areas |
| Protective Systems | 3. Seatbelt wearing rate in front seats<br>4. Seatbelt wearing rate in rear seats |
| Vehicle | **The age distribution**<br>5. Percentage of cars < 6 years<br>6. Median age of cars<br>**The composition**<br>7. Percentage of motorcycles in fleet<br>8. Percentage of heavy goods vehicles in fleet |
| Infrastructure | 9. Motorways density<br>10. Percentage of motorways in total road length |
| Trauma Management | 11. Health expenditure as a GDP % |

From the literature review that was conducted and as was presented in the preceding sections, most of the research and development towards a road safety performance index has focused predominantly on European countries. The previous literature has provided a solid background that will allow for this thesis to develop and analyze models for a wider range of countries. Through extensive research, the development and selection criteria of which RSPIs to use in the creation of such an index became evident. A list of previously used RSPIs was presented in section 2.1.3. Another conclusion arrived at from this literature review was that the ranking of the countries using the DEA method presented the highest correlation with current methods of evaluation and is therefore the preferred weighting method. As a result of this finding, this thesis has focused on using the data envelopment analysis method to evaluate the road safety performance level of various countries around the world. The use of the DEA method will help provide interesting insights and allow for valuable recommendations to policy makers as an efficiency level for current operations can be identified. These road safety levels can be used in the future for setting reasonable and practical benchmarks and targets with the purpose of improving these levels. Additionally, this thesis will look to see what effect the addition of extra input variables has on a country's efficiency level and ranking.

## 2.2 Accident Prediction Modeling

### *2.2.1 Development of Accident Prediction Models*

An extensive literature review indicates that very little work has been undertaken to find ways of improving road safety levels on a macroscopic level. Most previous work focuses on improving safety levels of a specific project or along a corridor using rather traditional modeling methods. Traditional methods, such as Black Spot programs, identify accident-prone locations on the basis of the total number of accidents and whether or not they exhibit a higher occurrence than an established “norm”. These methods do not take into consideration other possible contributing factors and do not provide any insight into whether these locations can be enhanced by making an improvement to the road or the law. Some researchers (Sayed et al., 1997; Sayed & Rodriguez, 1999; De Leur & Sayed, 2003; Hadayeghi, Shalaby, & Persaud, 2003; Ladrón de Guevara, Washington, & Oh, 2004; Lovegrove & Sayed, 2006; Sawalha & Sayed, 2006) have examined ways of identifying accident-prone locations by developing accident predication models using more proactive methods. These models were developed in the planning process and at a more macroscopic level using RSPIs. The use RSPIs allowed the models to consider other contributing factors.

Traditional programs, such as the Black Spot program, were typical safety programs that included the identification, diagnosis, and remedy of accident-prone locations. These programs started with a problem and attempted to find a solution. The modified Black Spot program approach developed Sayed et al. (1997) identified accident-prone locations by doing the reverse. The modified Black Spot program accounted for contributing factors and causes and used a fuzzy pattern recognition algorithm to do so. Accident-prone locations were identified by analyzing the representation of a particular accident pattern (e.g. mostly head on crashes, or mostly right angle crashes). If there was an overrepresentation of a specific pattern, the location was identified as accident-prone. The approach was applied to a set of signalized intersections in British Columbia, Canada using accident data from 1989 to 1991. By reversing the traditional

Black Spot approach and using a counter-based approach, they were able to first identify main accident patterns and then search for locations that exhibited an overrepresentation of these patterns. However, one of the downsides of using more traditional methods is that they require collision history, which doesn't always exist. There is another downside. Since the traditional methods do not consider possible contributing factors to the accidents, some locations that are not truly hazardous from a road safety authority perspective may be identified as accident-prone (Sayed et al., 1997). The empirical Bayes technique was used to discourage this type of identification (Sayed et al., 1997; Sayed & Rodriguez, 1999). This technique also accounts for random variations and regression-to-the-mean effects and provides a more accurate result for the calculated expected number of accidents. These counter-based approaches are not intended to replace the traditional methods but rather to provide a complementary way of identifying accident-prone locations and effective countermeasures.

Another way to enhance the traditional safety programs is with the development of statistically reliable accident prediction models. Accident prediction models use a more proactive approach and complement the more traditional reactive methods. They help prevent unsafe situation from arising in the first place. Sayed & Rodriguez (1999) developed accident prediction models for urban unsignalized intersections. De Leur & Sayed (2003) developed a framework to proactively consider road safety within the road planning process. Hadayeghi et al. (2003) developed a series of macrolevel accident prediction models that evaluated the safety of urban transportation systems. Ladrón de

Guevara et al. (2004) developed planning-level crash prediction models for Tucson, Arizona. Lovegrove & Sayed (2006) developed macro-level accident prediction models for evaluating neighbourhood traffic safety across neighbourhoods in the Greater Vancouver Regional District. Being able to address road safety concerns during the planning stages rather than after the road has been designed and built can be cost efficient. Determining the problems beforehand could save lives, which in turn leads to saving money since the loss of a human life is known to have high economic and social costs.

The objectives of the accident prediction models, as used by Lovegrove & Sayed (2006, p. 610), are as follows:

1. *to be a practical, feasible, macro-level, safety planning decision-support tool;*
2. *to facilitate a proactive approach to community planning that addresses road safety before problems emerge; and*
3. *to complement the more traditional, reactive road safety improvement methods.*

Two important transportation planning activities that rely on accident prediction models were discussed by Ladrón de Guevara et al. (2004). The first one was with regards to the Transportation Equity Act for the 21st Century (United States Department of Transportation, 1998), which requires metropolitan planning organizations and state departments of transportation to actively engage in proactive safety planning. The second activity related to the transportation agencies' need and desire to provide incentive programs to reduce the number of fatalities or injuries in a region. This, however, requires a forecast of what the safety levels are expected to look like some time down the road.

In their development of a systematic framework, De Leur & Sayed (2003) suggested that, “the first step in developing a systematic framework for proactive road safety planning is to understand the opportunities to provide safety input in the [design] process.” Exposure, probability, and consequence were listed as the three fundamental elements used to describe road safety risk. They established guiding principles to facilitate the consideration of proactive safety planning associated with each element and developed a framework based on these principles. A case study of an actual highway-planning project in British Columbia demonstrated the use of the framework. De Leur & Sayed (2003) concluded that using a more proactive approach and shifting focus from fixing existing road problems to helping plan roads will be a safer road system.

The accident prediction models developed by Sayed & Rodriguez (1999) were tested using four applications of the models: 1. identifying accident-prone locations; 2. developing critical accident frequency curves; 3. ranking the identified accident-prone locations; and 4. evaluating before-and-after studies. These applications were used to show the usefulness of the accident prediction models in assessing the safety of unsignalized intersections by conducting a case study using 419 urban unsignalized intersections in British Columbia, Canada. Each of the model’s four applications showed satisfactory goodness-of-fit. Hadayeghi et al. (2003) developed a series of models for the 463 traffic zones in the city of Toronto, Canada. Their objective was to help facilitate the estimation of road accidents on a more urban level. Data was assembled and obtained from three sources: the Traffic Data Centre of the city of Toronto, the Transportation Tomorrow Survey, and the Transportation Section, Department of Civil Engineering, University of Toronto. Two separate models were developed, one model for total accidents and one for severe (fatal and nonfatal injury) accidents. Each model was developed based on data related to major and minor arterial roads in each zone rather than a function of its traffic intensity and other characteristics. The models were a function of socioeconomic and demographic variables, traffic demand variables, and network data variables. Ladrón de Guevara et al. (2004) used the Pima Association of Governments' traffic analysis zone digital map to divide the Tucson area up into 859 different traffic analysis zones. This map was created using geographic information systems (GIS) – an application that has not often been applied in safety applications. The socio-demographic and socioeconomic variables dataset was obtained from Pima County and the city of Tucson. The researchers developed three types of models: one fatal crash model, two injury accident models, and one property damage accident model. In addition to the above models, a simultaneous negative binomial model was developed for the fatal and injury models. Even though they were able to show that it was possible to estimate meaningful accident prediction models, they stated that the models were intended to provide safety forecasts at a zonal level and not at a road network or project level, as they do not consider the usual explanatory variables found in such models. For that reason, these models should be applied for long-range approximate forecasts and not for countermeasure selection or policy decisions.

Lovegrove & Sayed (2006) developed macro-level accident prediction models for evaluating neighbourhood traffic safety across 577 neighbourhoods in the Greater Vancouver Regional District. Data was collected from three sources: TransLink (the Greater Vancouver Regional District transportation authority), Census Canada, and the Insurance Corporation of British Columbia. With the obtained data, they developed 35 accident prediction models (11 exposure models, eight socio-demographic models, seven transportation demand management models, and eight network models). They showed that it was possible to quantify a statistically predictive association between traffic safety and neighbourhood characteristics pertaining to traffic exposure, socio-demographic, transportation demand management, and road network on a macro-level.

Previous literature carefully considered what methodology to use to develop these accident prediction models as well as what error structure to consider. Generally, the research discussed two modeling approaches: traditional linear modeling (normal distribution) and generalized linear modeling (Poisson and negative binomial error structure). Since road accidents are rare and random events, the data cannot be assumed to be normally distributed and can therefore not be linear so the generalized linear modeling approach was more appropriate. Sayed & Rodriguez (1999), Hadayeghi et al. (2003), Ladrón de Guevara et al. (2004), and Lovegrove & Sayed (2006) all developed their accident prediction models using a generalized linear modeling approach with a negative binomial error structure. Chapter 4 will discuss the differences between the approaches and the error structures in greater detail and will explain why a negative binomial error structure is preferred over a Poisson error structure.

Sawalha & Sayed (2006) examined some statistical issues that are associated with the development of traffic accident modeling. Accident prediction models have become valuable tools in the study of road safety analysis because they have the ability to estimate the safety of a potential road entity, identify and rank accident-prone locations, and evaluate the effectiveness of remedial measures. To develop such model, one uses statistical modeling. Typically, the models are developed with the use of a statistical analysis software program. Even though a software program is used, some statistical issues still exist. Their work investigated two issues that may affect accident models that use Poisson and negative binomial regression as their error structure. The two statistical issues are: model building (deciding which explanatory variables to include in the model), and outlier analysis. Firstly, determining which explanatory variables should be included in the model can be a tough decision. The main thing is that the variables should relate to the issue in question. Once certain variables have been selected, statistical determination helps decide whether the variable should remain in the model. There are goodness-of-fit measures like the Pearson chi-square value and the scaled deviance that can help with this decision. It is beneficial to include statistically significant variables in the model as they will assist with the explanation of the variability of accident data and help improve the fit of the model. However, just because a variable is significant does not mean it is justified to include the variable in the model. As researchers develop models with the hope of using them for an unlimited number of locations, the number of variables may have to be limited. This is because accident data might not be available for every variable of a location that future researchers may want to study. They suggested using the principle of parsimony, which "calls for explaining as much of the variability of the data using the least number of explanatory variables." This method helps avoid over-fitting. Therefore, if the model is to be applied to a number of different locations, you want to make sure it can produce reliable predictions and so the number of explanatory variables may have to be limited. If the model were solely developed for one particular set of locations, including all the significant variables would provide a more accurate result. The paper discusses procedures for building parsimonious and best-fit models.

The second issue dealt with outlier analysis. An outlier is considered an extreme or unusual observation in a dataset. Sometimes this is due to a recording error and sometimes it is just genuinely different from the other observations. Outliers can have a significant effect on the results if not dealt with correctly. If an error is found in the dataset, it can be corrected. If the value is genuinely different from the others and has an extreme influence on the model equation, however, this paper suggests that it should be removed from the model development. It is important that these outliers are investigated and not just deleted from that database, as there could be an explanation for it. The paper discusses a procedure for identifying outliers that should be excluded from the model development. The procedures were tested out by developing accident prediction models with data from 58 urban arterial roads in the cities of Vancouver and Richmond, Canada. The study presented enough justification in defense of the validity of the procedures.

### *2.2.2 RSPIs Used in the Development of APMs in Previous Literature*

This section will provide a brief overview of what explanatory variables (RSPIs) have been considered in previous literature for the development of accident prediction models (APMs) at a zonal level.

Hadayeghi et al. (2003) developed four models using vehicle kilometers travelled as the exposure variable. The total accident model, the severe accident model, and the morning peak accident models included the following explanatory variables: major road kilometer, number of households, posted speed, volume/capacity, and intersection density. Table 5 is a list of explanatory variables initially considered by Hadayeghi et al. (2003) before selection (*Transportation Research Record: Journal of the Transportation Research Board, No. 1840,* Table 1, p. 90. © National Academy of Sciences, Washington, D.C., 2003, adapted with permission).

**Table 5 – List of explanatory variables considered by Hadayeghi et al. (2003)**

| Variable Type | Variable |
|---|---|
| Socioeconomic and demographic | • Total population<br>• Population density<br>• Number of households<br>• Household density<br>• Full-time employed<br>• Part-time employed<br>• Total employed<br>• Employment density<br>• Number of vehicles<br>• Number of vehicles per household |
| Network or supply | • Number of intersections<br>• Intersection density<br>• Major road kilometers<br>• Mino road kilometers<br>• Total road kilometers<br>• Area |
| Traffic demand | • Posted speed<br>• Volume/capacity<br>• In-flow<br>• Out-flow<br>• Vehicle kilometers travelled<br>• Total flow |
| Dependent variables | • Total accidents<br>• Severe accidents<br>• Total accidents, morning period<br>• Severe accidents, morning period |

The models developed by Ladrón de Guevara et al. (2004) contain socio-demographic and socioeconomic variables. The fatal crash model considered the following three independent variables: population density, people 17 years old or younger, and intersection density. Two injury accident models were developed. The first one used population density as its exposure variable and the second model used vehicle miles travelled. They included the following explanatory variables: miles of principal arterial-other as a percentage of street road network, miles of minor arterial as a percentage of street road network, and miles of urban collectors as a percentage of street road network. The property damage accident model used the same variables as the injury crash model with population density as its exposure variable. Table 6 is a list of explanatory variables considered by Ladrón de Guevara et al. (2004) (*Transportation Research Record: Journal of the Transportation Research Board, No. 1897,* Table 1, p. 193. © National Academy of Sciences, Washington, D.C., 2004, adapted with permission).

**Table 6 – List of variables considered by Ladrón et al. (2004)**

| | Variables |
|---|---|
| **1.** | Transportation analysis zone |
| **2.** | Number of accidents |
| **3.** | Number of fatal accidents |
| **4.** | Number of injury accidents |
| **5.** | Number of property-damage accidents |
| **6.** | Area of traffic analysis zone (acres) |
| **7.** | Number of people |
| **8.** | Number of people/acre |
| **9.** | Population per occupied housing unit |
| **10.** | Number of occupied housing units |
| **11.** | Vehicle miles traveled |
| **12.** | Number of housing units/acre |
| **13.** | Persons 17 years old or young as a percentage of the total population |
| **14.** | Persons aged 65 years old or older as a percentage of the total population |
| **15.** | Ratio of youths (17 years or younger) and elderly (65 years or more) to working age persons (18-64 years) |
| **16.** | Number of employees |
| **17.** | Civilian, noninstitutionalized persons 15 years and older with a disability as a percentage of all civilians |
| **18.** | Vacant housing units as a percentage of all housing units |
| **19.** | Occupied housing units with no vehicle available as a percentage of all occupied units |
| **20.** | Number of elementary schools |
| **21.** | Number of middle schools |
| **22.** | Number of high schools |
| **23.** | Number of colleges |
| **24.** | Number of universities |
| **25.** | Number of schools (all types) |
| **26.** | Number of police stations |
| **27.** | Number of intersections/acre |
| **28.** | Number of bus stops/acre |
| **29.** | Number of intersections |
| **30.** | Number of bus stops |
| **31.** | Miles of signed bike route w/on |
| **32.** | Miles of bike route on multiuse path |
| **33.** | Miles of bike route on bus lane |
| **34.** | Miles of signed bike route |
| **35.** | Miles of bike route with paved shoulder |
| **36.** | Miles of bike route on residential streets |
| **37.** | Miles of bike route for experienced riders |
| **38.** | Total miles of bus route |
| **39.** | Miles of principal arterial interstate as a percentage of street road network |
| **40.** | Miles of principal arterial expressway as a percentage of street road network |
| **41.** | Miles of principal arterial-other as a percentage of street road network |
| **42.** | Miles of minor arterial as a percentage of street road network |
| **43.** | Miles of major collector rural as a percentage of street road network |
| **44.** | Miles of minor collector rural as a percentage of street road network |
| **45.** | Miles of urban collectors as a percentage of street road network |
| **46.** | Miles of street network |

The 35 accident prediction models developed by Lovegrove & Sayed (2006) considered five exposure variables and RSPIs in the following categories: socio-demographics, transportation demand management, and network. As outputs, they included total accidents over 3 years and severe accidents (fatal and injury). Table 7 (Lovegrove, G. R. & Sayed, T., Macro-level accident prediction models for evaluating neighbourhood traffic safety, Canadian Journal of Civil Engineering, 33(5), 609-621, © 2008 Canadian Science Publishing or its licensors, reproduced with permission) lists the exposure variables and the RSPIs used in the development of the 35 models.

**Table 7 – Exposure variables and RSPIs used by Lovegrove & Sayed (2006)**

| Variable Type | Variables |
|---|---|
| Exposure | • Total transit and vehicle kilometers travelled<br>• Total lane kilometers<br>• Average congestion level (VC)<br>• Average speed<br>• Total area |
| Socio-demographics | • Average zonal family size<br>• Home density<br>• Zonal residents<br>• Population density<br>• Residents working in tourism, retail, government, and construction |
| Transportation demand management | • Total commuters from each zone<br>• Commuter density<br>• Core area<br>• Core area as a percentage of total zonal area<br>• Shortcut capacity on local roads through zone<br>• Shortcut capacity, with VC used to adjust “attractiveness”<br>• Number of drivers commuting from zone |
| Network | • Number of signals<br>• Signal density<br>• Number of intersections<br>• Intersection density<br>• Number of intersections per lane kilometers<br>• Percentage of three-way intersection per intersection<br>• Percentage of arterial-local intersections per intersection<br>• Percentage of arterial lane kilometers per total lane kilometers<br>• Percentage of local lane kilometers per total lane kilometers |

Since little to no research has been done to develop accident prediction models at a global level, it should be noted that these RSPIs were not all relevant in the model development for this thesis. A description of the variables used in the models in this thesis will be discussed in Chapter 4.

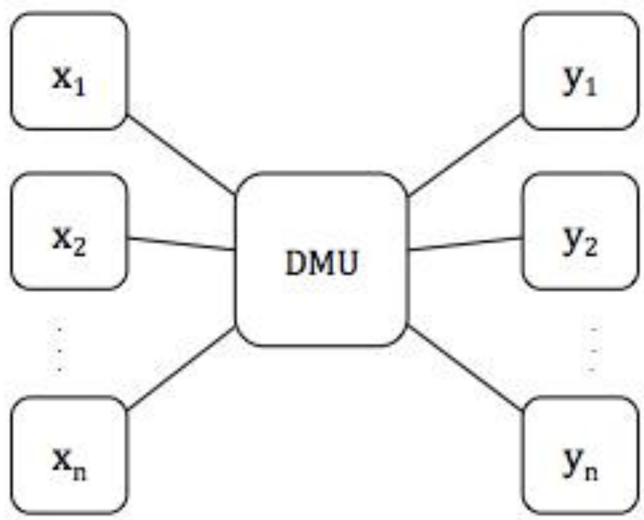
# 3. Data Envelopment Analysis

Finding additional ways to evaluate the road safety performance of different countries, other than using the traditional method of the number of fatalities per million inhabitants, has become an important issue. This chapter will be discussing the development of a composite road safety performance index with the use of the data envelopment analysis (DEA) weighting method. Section 3.1 will explain the methodology behind the technique, section 3.2 discusses what data will be used and what sources were considered, and section 3.3 presents the analysis and results.

## 3.1 Methodology

This section will discuss the development of the data envelopment analysis (DEA) model. DEA is an evaluation technique developed by Charnes, Cooper, & Rhodes (1978). It is a performance measurement technique that can be used to evaluate the relative efficiency of decision making units (DMUs). The efficiency of a DMU is obtained as the maximum ratio of the weighted sum of outputs to the weighted sum of inputs where the ratio lies between zero and one. A DMU with a ratio of one is considered efficient and anything lower is considered inefficient. Each DMU set contains $x$ inputs and $y$ outputs (Figure 1). In this study, each DMU refers to a country.

**Figure 1 – DMU structure**




The model used by Charnes et al. (1978) to determine the efficiency score, $E_0$, is as follows:

$$\max E_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \tag{1}$$

$$s.t. \qquad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \qquad j = 1, \dots, n$$

$$u_r, v_i \geq 0, \quad r = 1, \dots, s, \quad i = 1, \dots, m$$

In this model, $y_{rj}$ and $x_{ij}$ are the $r^{th}$ output and the $i^{th}$ input, respectively of the $j^{th}$ DMU. The weights for the $r^{th}$ output and the $i^{th}$ input are $u_r$ and $v_i$, respectively. The optimal weights for each DMU will be determined by the data on all of the DMU's which are being used as a reference set and will ensure a maximized efficiency ratio for each DMU.

This model can be further simplified by constraining the weighted sum of inputs to a value of one so as to maximize the weighted sum of outputs (Charnes et al., 1978):

$$\max E_0 = \sum_{r=1}^{s} u_r y_{r0} \tag{2}$$

$$s.t. \qquad \sum_{i=1}^{m} v_i x_{i0} = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad j = 1, \dots, n$$

$$u_r, v_i \geq 0, \quad r = 1, \dots, s, \quad i = 1, \dots, m$$

From an economic perspective, one aspires to minimize the inputs and maximize the outputs, but when it comes to road safety, one actually wants the opposite – maximized inputs and minimized outputs. Therefore, as suggested by Hermans et al. (2009), the ratio of the weighted output over the weighted input should be minimized rather than maximized (e.g. the number of fatalities per million inhabitants (output) can be minimized by maximizing the seatbelt-wearing rate (input)).

Hermans et al. (2009) devised a linear model to calculate the efficiency score of a country where the sum of *k* weighted output values of a country *j* is minimized by setting the sum of *l* weighted input values of a country *j* equal to one. There are three constraints. The first constraint is that the sum of the weighted inputs ($w_i x_{ij}$) must equal one. The second constraint requires that the weighted sum of the outputs ($w_o y_{oj}$) minus the weighted sum of the inputs is positive. The third constraint states that the input weights ($w_i$) and output weights ($w_o$) must also be positive. The model is formulated as follows:

$$SCORE_j = min \sum_{o=1}^{k} w_o y_{oj} \tag{3}$$

$$s.t. \qquad \sum_{i=1}^{l} w_i x_{ij} = 1$$

$$\sum_{o=1}^{k} w_o \, y_{om} - \sum_{i=1}^{l} w_i x_{im} \geq 0, \qquad m = 1, \ldots, n$$

$$w_o, w_i \geq 0, \quad i = 1, \ldots, l, \quad o = 1, \ldots, k$$

Using the DEA model presented in equation (3), efficiency scores for each country will be calculated using the LINGO software developed by Lindo Systems Inc. (2007). An example of the LINGO code can be found in Appendix A. The best performing country will receive a *SCORE* of one and an underperforming country will receive a score greater than one. The sources and the amount of inefficiency in each indicator can be identified from the country specific weights. It should be noted that dimensions on which a country performs well will receive a higher weight and that the weighting values do not add up to one. Underperforming countries can use the values of efficient countries as targets to improve their score or standing amongst the other countries in the dataset. This method does not require normalization of the indicators as it can handle raw values. Each country will end up with its own set of indicator weights rather than there being one set of weights for all countries. The DEA method compares the results of a country relative to the other countries in the dataset. This means that the results of one analysis cannot be compared with another analysis unless they both consider the same number of countries.

## 3.2 Data

This study considers two analyses – Analysis 1 and Analysis 2 – and each of these contains a sub-analysis. While the main purpose of the study is to calculate an efficiency score for each country, which will then be used for ranking, it will also investigate if the addition of an extra input variable has any effect on the efficiency scores and the ranking. The main analysis – calculating efficiency scores and ranking – will be carried out for 36 countries in Analysis 1 and 24 countries in Analysis 2. The reason behind the difference in the number of countries will be explained later. The countries for each analysis are listed in Table 8. The data for each country can be found in Appendix B. Subsequently to the main analysis, the sub-analyses will look to compare the efficiency scores and rankings of the countries using one or two additional input variables.

**Table 8 – List of countries for Analysis 1 and Analysis 2**

| ANALYSIS 1 | ANALYSIS 2 |
|---|---|
| 1. Australia | 1. Australia |
| 2. Austria | 2. Austria |
| 3. Belgium | 3. Belgium |
| 4. Canada | 4. Chile |
| 5. Chile | 5. Cyprus |
| 6. Cyprus | 6. Ecuador |
| 7. Czech Republic | 7. Estonia |
| 8. Ecuador | 8. Finland |
| 9. Estonia | 9. France |
| 10. Finland | 10. Hungary |
| 11. France | 11. Iceland |
| 12. Germany | 12. Ireland |
| 13. Greece | 13. Israel |
| 14. Hungary | 14. Japan |
| 15. Iceland | 15. Mauritius |
| 16. Ireland | 16. Morocco |
| 17. Israel | 17. New Zealand |
| 18. Italy | 18. Norway |
| 19. Japan | 19. Oman |
| 20. Latvia | 20. Poland |
| 21. Malta | 21. Sweden |
| 22. Mauritius | 22. Switzerland |
| 23. Morocco | 23. United Kingdom |
| 24. Netherlands | 24. United States |
| 25. New Zealand | |
| 26. Norway | |
| 27. Oman | |
| 28. Peru | |
| 29. Poland | |
| 30. Romania | |
| 31. Serbia | |
| 32. Spain | |
| 33. Sweden | |
| 34. Switzerland | |
| 35. United Kingdom | |
| 36. United States | |

The purpose of the sub-analysis in Analysis 1 is to compare the efficiency scores and rankings of its 36 countries by examining the following two options: (a) three input variables and two output variables, and (b) four input variables and two output variables. Option (a) considers the following three input variables: the percentage of seatbelt use in front seats, the road density, and the total health expenditure as a percentage of the gross domestic product. Option (b) uses the same three input variables as above but adds a fourth input variable: the percentage of seatbelt use in rear seats. The two output variables considered are: the number of fatalities per million inhabitants and the number of fatalities per million passenger cars. The aim of the sub-analysis in Analysis 2 is to compare the efficiency scores and rankings of its 24 countries by examining the following three options: (a) three input variables and two output variables, (b) four input variables and two output variables, and (c) five input variables and two output variables. Options (a) and (b) are the same as in Analysis 1. Option (c) includes the addition of a fifth input variable: the percentage of total roads paved. The two output variables also remain the same as in Analysis 1. The reason behind the use of these particular variables will be discussed later on.

Data for the input and output variables were collected from various international sources, including the World Databank (2012) and the World Health Organization (WHO) (2009; 2012a). Inside the World Databank, data was collected from the World Development Indicators and Global Development Finance database. Data obtained from WHO was found in the Data and Statistics database for Road Safety. To have accurate results, it is important to use the most up-to-date values. Thus, this study used data from the year 2007 since this was the most recent data available at the time of analysis.

A few limitations were encountered during the selection process of the input and output variables and the countries – although the selection of countries is highly dependent on the available data. Firstly, one of the requirements for using the DEA method is that each input variable follows the same direction and each output variable follows the same direction. In this study, this meant that each input variable had to be set up so that it could be maximized and each output variable had to be set up so it could be minimized. This requirement can bring on a complication during the variable selection process and limit the number of variables that could be considered, as some of the variables may not be able to reverse their direction. Secondly, as previously mentioned, the number of countries used in the analysis is highly dependent on the availability of the data. If a country does not have a complete dataset for the variables under consideration it must be eliminated from the analysis. Therefore, if a certain variable only has limited data available, it may sometimes be best to just eliminate that variable.

Studies have shown that there are many factors that increase the probability of accidents occurring (Al Haji, 2005). It can be said that if a change in a factor causes a simultaneous change (increase or decrease) in the number of accidents, that there is a correlation between the two factors. Al Haji (2005) provided a summary of the most important risk factors. He made use of the *Handbook of Road Safety* Measures by Elvik & Vaa (2004) which provides a summary of many road safety measures whose effects were evaluated and quantified in different studies for countries around the world. The variable selection process started with data for the 178 WHO member countries using the 15 input variables and six output variables listed in Table 9. It is important that these variables have a significant effect on road traffic fatalities, which in this case, they do. The first input variable belongs to the alcohol risk domain. Hakkert & Braimaister (2002) as well as Thoresen, Fry, Heiman, & Cameron (1992) showed that the risk in traffic increases rapidly with a BAC (Blood Alcohol Content). The effect here is that drivers with a high BAC in their blood have a greater chance of being killed than drivers with no BAC in their blood. The second and third input variables belong to the speed risk domain. The relation here is that higher speeds increase the risk of an accident as well as the severity of the accident. Excessive speed is the biggest contributor to the number of fatalities on the roads in many countries (OECD/ECMT, 2006) Studies and reports have shown that the number of pedestrian accidents and injuries can be significantly influenced by vehicle speeds (Leaf & Preusser, 1999; OECD/ECMT, 2006). Studies have also shown that the risk of a fatality in a road accident can double by speeds just 5 km/h above average in 60 km/h urban areas, and 10 km/h above average in rural areas (Australian Transport Council, 2008). Input variables four through six belong to the protective systems risk domain. Research has found that the use of seat belts can significantly reduce road fatalities. Elvik & Vaa (2004) showed that the probability of drivers or front seat passengers being killed was reduced by 40-50% with the use of seat belts. They also showed that this probability was reduced by 25% for passengers in the back seat. The *World Report on Road Traffic Injury Prevention* by the World Health Organization (2004) stated that the use of motorcycle helmets reduces fatalities and serious injuries by 20% and 45%, respectively. Input variables seven through ten belong to the vehicles risk domain. As stated in *Deliverable 3.7a* of the *SafetyNet report* (Vis & Van Gent, 2007, p. 34), fleet composition gives “an indication of the safety of a fleet since there are issues of vehicle-to-vehicle compatibility that have a well-recognised effect on occupant outcomes in crashes." The size and mass of the vehicles involved in an accident can be crucial to the outcome. A car-to-car crash provides more of an equal occupant protection compared to a truck-to-car crash. A truck-to-car crash would increase the risk of a road fatality. Input variables 11 and 12 belong to the infrastructure (or roads) risk domain. Road density and the percentage of roads paved both have an effect on safety. WHO (2004) stated that road networks influence accident risk as it affects how road users perceive the environment. The road density value is defined by the total length of the road network divided by the surface area of the country. A high road density would imply that the road users have ample access to an actual road. Traveling on a road surface would be safer than traveling through a field or a park. When it comes to the percentage of roads paved, research has shown that poor road surface conditions contribute to an increased accident risk (ETSC, 2001; Al Haji, 2005). For this reason, a greater percentage of paved roads would mean a better road surface which could lead to a reduction in the number of road accident fatalities. Lastly, the last three input variables belong to the trauma management risk domain. Al Haji (2005) discussed studies that showed how fatality rates are correlated with the level of medical facilities available in a country. It is reasonable to assume that a country with a higher health expenditure budget as well as more medical staff and more hospital beds (per 1000 people) could provide better care to the victims of a road traffic accident. This better care could result in a reduction in the number of road traffic fatalities.

**Table 9 – Input and output variables (before selection)**

| INPUT VARIABLES | OUTPUT VARIABLES |
|---|---|
| 1. Attribution of Road Traffic Deaths to Alcohol (%)<br>2. Maximum Speed Limit – Urban Roads<br>3. Maximum Speed Limit – Rural Roads<br>4. % Seatbelt Use Front Seats<br>5. % Seatbelt Use Rear Seats<br>6. % Helmet Usage by Motorcyclists<br>7. % of Motorcars of Fleet<br>8. % of Motorized 2- and 3-wheelers of Fleet<br>9. % of Trucks of Fleet<br>10. % of Buses of Fleet<br>11. Road Density (km/1000 km^2)<br>12. Roads, paved (% of total roads)<br>13. Health Expenditure, total (% of GDP)<br>14. Medical Staff (per 1,000 people)<br>15. Hospital Beds (per 1,000 people) | 1. Number of Fatalities per Million Inhabitants<br>2. Fatalities per Million Passenger Cars<br>3. Fatalities per 10 Billion Passenger-km Traveled<br>4. % Pedestrian Fatalities<br>5. % Cyclist Fatalities<br>6. % Motorcyclist Fatalities |

The first data filtration consisted of making sure that the input and output variables were set up to allow for maximization and minimization, respectively. This immediately required the removal of six input variables, since these could not be set up in a way that allowed for maximization. The six variables included the maximum speed limit on urban and rural roads, and the fleet composition (% of motorcars, % of motorized 2- and 3-wheelers, % of trucks, % of buses). Once this was done, the second filtration process was implemented. For the remaining nine variables, all blanks were carefully filtered and removed from the Excel spreadsheet so as to determine complete datasets. Doing this led to the realization that there would only be six countries with complete datasets remaining when considering all nine input variables. This was of course not acceptable. Variables that had little data available were then deleted to further assist with the selection process. It was decided that the most acceptable amount of input variables to be used was five as this led to a remaining 24 countries. These five input variables were: percentage of seatbelt use in front seats, percentage of seatbelt use in rear seats, road density, total health expenditure as a percentage of GDP, and percentage of total roads paved. Removing the *percentage of total roads paved* input variable increased the number of countries to 36 and the removal of the *percentage of seatbelt use in rear seats* input variable increased the number of countries once more, to 42.

This led to the decision to conduct two separate analyses – one using three and four input variables with 36 countries and one using three, four, and five input variables with 24 countries. The reason behind the sequence of the chosen input variables lies in the fact that the three initial input variables resulted in the highest number of countries and each additional input variable reduced this number. It could be supposed that this indicates that the three input variables are the most noteworthy since more countries have collected data for this variable but it more than likely has to do with the ease of collecting data for these variables. The same could be said for the sequence of the second analysis. In order for a comparison between options to be acceptable, the different options have to use the same number of countries, as the efficiency score is relative to the data available for the other countries in the dataset. This explains why there is no analysis using the 42 countries. The motive behind using only the first two output variables is because of the lack of data for the other four variables in addition to the fact that the first two variables have been used in previous literature and would allow for an easier comparison between this study and previous work.

It can therefore be stated that the addition of input variables increases the risk of eliminating countries from the dataset as less data becomes available. The explanations above describe the reason behind the difference in the number of countries between Analysis 1 and Analysis 2 as the addition of an input variable or two lead to a decrease in complete datasets resulting in less available countries. The lack of available data can be attributed to the fact that there is currently no global standard on what data should be collected and some countries have limited resources to collect such data and therefore may not do so.

## 3.3 Analysis and Results

In this section, the DEA analysis results are presented. As discussed earlier, the main purpose of this study was to elaborate on the ways of evaluating road traffic safety performance levels of countries around the world. This is achieved using the DEA method to calculate efficiency scores and respectively rank those countries. In addition to the ranking, the study investigated if the addition of an input variable has any effect on efficiency scores and ranking. Efficiency scores can be used to identify benchmarks and set targets for countries that are underperforming. Ranking of the countries essentially has the same purpose. It gives the countries a better idea of how they are performing compared to other countries in the dataset.

### *3.3.1 Efficiency Scores*

Table 10 presents the efficiency scores of the 36 countries in Analysis 1 after running the DEA analysis with the LINGO software (Lindo Systems Inc., 2007). It can be seen that Malta is the best performing country in both cases – three and four inputs – as it obtained the optimal efficiency score of 1.000. In the first case, Malta is the only country to receive a score of one while the other 35 countries obtain a score higher than one and are therefore considered underperforming countries. With the addition of a fourth input variable, it can be seen that the Netherlands, Sweden, and Switzerland join Malta as efficient countries by also obtaining an optimal efficiency score of 1.000. All four of these countries are now considered to be the best performing countries amongst the 36 countries.

**Table 10 – Efficiency scores for Analysis 1**

| COUNTRY | SCORE 3 INPUTS |
|---|---|
| Malta | 1.0000 |
| Switzerland | 1.2853 |
| Netherlands | 1.3566 |
| Norway | 1.5662 |
| Sweden | 1.5916 |
| Germany | 1.5967 |
| Japan | 1.6563 |
| United Kingdom | 1.7499 |
| France | 1.8292 |
| Israel | 1.8526 |
| Austria | 2.2747 |
| Iceland | 2.3860 |
| Australia | 2.4320 |
| Canada | 2.4558 |
| Finland | 2.4561 |
| United States | 2.6169 |
| Belgium | 2.7856 |
| Italy | 2.8342 |
| New Zealand | 2.8906 |
| Ireland | 2.9321 |
| Spain | 2.9492 |
| Cyprus | 3.0978 |
| Serbia | 3.5409 |
| Mauritius | 3.6032 |
| Czech Republic | 3.9594 |
| Greece | 4.1950 |
| Hungary | 4.3593 |
| Peru | 4.4919 |
| Romania | 4.7374 |
| Estonia | 4.9091 |
| Morocco | 4.9936 |
| Ecuador | 5.1209 |
| Chile | 5.4160 |
| Poland | 5.8985 |
| Latvia | 6.9139 |
| Oman | 10.0793 |

| COUNTRY | SCORE 4 INPUTS |
|---|---|
| Malta | 1.0000 |
| Netherlands | 1.0000 |
| Sweden | 1.0000 |
| Switzerland | 1.0000 |
| Norway | 1.0087 |
| Germany | 1.0361 |
| United Kingdom | 1.0468 |
| Australia | 1.2564 |
| France | 1.2732 |
| Israel | 1.5070 |
| New Zealand | 1.5176 |
| Finland | 1.5450 |
| Iceland | 1.5527 |
| Japan | 1.6565 |
| Canada | 1.6754 |
| Austria | 1.9356 |
| Ireland | 2.0428 |
| Spain | 2.0533 |
| United States | 2.2281 |
| Belgium | 2.4066 |
| Czech Republic | 2.4809 |
| Italy | 2.8345 |
| Cyprus | 3.0980 |
| Estonia | 3.3638 |
| Serbia | 3.5415 |
| Mauritius | 3.6036 |
| Hungary | 3.6851 |
| Greece | 3.7370 |
| Peru | 4.2361 |
| Chile | 4.4014 |
| Poland | 4.4739 |
| Romania | 4.6222 |
| Morocco | 4.8609 |
| Ecuador | 5.1213 |
| Latvia | 5.9970 |
| Oman | 10.0811 |

A study conducted by Shen et al. (2012) using 27 European countries showed a similar result for Malta as it tied with the United Kingdom as the best performing country. In addition to the DEA-based road safety (DEA-RS) model developed by the researchers, they also developed a cross-efficiency model which they used to identify the best overall performers. Once developed and efficiency scores were calculated, they determined the standard deviation between the two sets of efficiency scores. Malta obtained the highest standard deviation value indicating that it had the highest level of uncertainty between the two scores amongst the other countries. They attribute this to the allocation of unreasonable weights in the DEA-RS model. As a result, during the clustering stage, they decided to put Malta in a cluster of its own and eventually decided to exclude it due to its high difference and lack in similarity with other countries.

Table 11 and Table 12 show the country specific weights of each RSPI for the model with 3 inputs and the model with 4 inputs of Analysis 1, respectively. Canada will be used as an illustration to explain the meanings of these weights. As can be seen in Table 11, for 3 input variables, Canada received its highest weight (0.09940) in the total health expenditure category. This means that Canada performed well in this category. In the other two categories, percentage of seat belt use in front seats and road density, Canada only received the minimum weight of 0.00001. Since a weight cannot have a value of zero, bounds had to be set. It can be seen in the sample code in Appendix A that the minimum weight was specified to be 0.00001. Since the DEA analysis method looks for the best possible combination of weights, any variable that received a weight of 0.00001 is considered ineffective. In Table 12, Canada still received its highest weight (0.04064) in the total health expenditure category but it is lower than in the 3-input analysis. The addition of the fourth input variable, the percentage of seat belt use in rear seats, received a weight of 0.00678 indicating that Canada also performed well in this category. The weights for the percentage of seat belt use in front seats and road density categories remained at 0.00001. Table 11 also shows that the highest country specific weight was either in the percentage of seat belt use in front seats category or the total health expenditure category with most of them being in the total health expenditure category. In Table 12, the highest country specific weight varied between the percentage of seat belt use in front seats category, the percentage of seat belt use in rear seats category, and the total health expenditure category with about an even split between the percentage of seat belt use in rear seats category and the total health expenditure category. None of the countries in Analysis 1 received a highest weight value in the road density category. Hermans et al. (2009) show how a set of weights for an underperforming country can be used to determine how much change is needed to make it a more efficient country.

**Table 11 – Country specific weights: 3 inputs (Analysis 1)**

| Location | Seat Belt | Road Safety | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | Road Density (km/1000 km^2) | Health Expenditure, total (% of GDP) | Number of Fatalities per Million Inhabitants | Fatalities per Million Passenger Cars |
| Australia | 0.01030 | 0.00001 | 0.00001 | 0.03170 | 0.00001 |
| Austria | 0.00001 | 0.00001 | 0.09679 | 0.02731 | 0.00001 |
| Belgium | 0.00001 | 0.00001 | 0.09842 | 0.02772 | 0.00001 |
| Canada | 0.00001 | 0.00001 | 0.09940 | 0.02796 | 0.00001 |
| Chile | 0.00001 | 0.00001 | 0.14470 | 0.03942 | 0.00001 |
| Cyprus | 0.01218 | 0.00001 | 0.00001 | 0.03698 | 0.00001 |
| Czech Republic | 0.01093 | 0.00001 | 0.00001 | 0.03346 | 0.00001 |
| Ecuador | 0.00001 | 0.00001 | 0.14351 | 0.03912 | 0.00001 |
| Estonia | 0.01097 | 0.00001 | 0.00001 | 0.03358 | 0.00001 |
| Finland | 0.00001 | 0.00001 | 0.12391 | 0.03416 | 0.00001 |
| France | 0.00001 | 0.00001 | 0.08866 | 0.02525 | 0.00001 |
| Germany | 0.00001 | 0.00001 | 0.09369 | 0.02652 | 0.00001 |
| Greece | 0.00001 | 0.00001 | 0.10078 | 0.02831 | 0.00001 |
| Hungary | 0.00001 | 0.00001 | 0.12939 | 0.03555 | 0.00001 |
| Iceland | 0.00001 | 0.00001 | 0.10718 | 0.00001 | 0.01650 |
| Ireland | 0.01147 | 0.00001 | 0.00001 | 0.03498 | 0.00001 |
| Israel | 0.01090 | 0.00001 | 0.00001 | 0.03338 | 0.00001 |
| Italy | 0.00001 | 0.00001 | 0.11380 | 0.00001 | 0.01742 |
| Japan | 0.01035 | 0.00001 | 0.00001 | 0.03185 | 0.00001 |
| Latvia | 0.00001 | 0.00001 | 0.14162 | 0.03864 | 0.00001 |
| Malta | 0.00001 | 0.00001 | 0.10428 | 0.02920 | 0.00001 |
| Mauritius | 0.01053 | 0.00001 | 0.00001 | 0.03235 | 0.00001 |
| Morocco | 0.01332 | 0.00001 | 0.00001 | 0.04016 | 0.00001 |
| Netherlands | 0.00001 | 0.00001 | 0.09983 | 0.02807 | 0.00001 |
| New Zealand | 0.01049 | 0.00001 | 0.00001 | 0.00001 | 0.01776 |
| Norway | 0.00001 | 0.00001 | 0.11390 | 0.03163 | 0.00001 |
| Oman | 0.01051 | 0.00001 | 0.00001 | 0.03229 | 0.00001 |
| Peru | 0.01175 | 0.00001 | 0.00001 | 0.03578 | 0.00001 |
| Poland | 0.01335 | 0.00001 | 0.00001 | 0.04025 | 0.00001 |
| Romania | 0.01240 | 0.00001 | 0.00001 | 0.03758 | 0.00001 |
| Serbia | 0.00001 | 0.00001 | 0.09605 | 0.02712 | 0.00001 |
| Spain | 0.00001 | 0.00001 | 0.11627 | 0.03223 | 0.00001 |
| Sweden | 0.00001 | 0.00001 | 0.11097 | 0.03089 | 0.00001 |
| Switzerland | 0.00001 | 0.00001 | 0.09246 | 0.02621 | 0.00001 |
| United Kingdom | 0.00001 | 0.00001 | 0.11669 | 0.03234 | 0.00001 |
| United States | 0.00001 | 0.00001 | 0.06182 | 0.01846 | 0.00001 |

**Table 12 – Country specific weights: 4 inputs (Analysis 1)**

| Location | Seat Belt | | Road Safety | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | % Seat Belt Use Rear Seats | Road Density (km/1000 km^2) | Health Expenditure, total (% of GDP) | Number of Fatalities per Million Inhabitants | Fatalities per Million Passenger Cars |
| Australia | 0.00001 | 0.01085 | 0.00001 | 0.00001 | 0.00001 | 0.00891 |
| Austria | 0.00001 | 0.00776 | 0.00001 | 0.05947 | 0.01497 | 0.00423 |
| Belgium | 0.00001 | 0.00637 | 0.00001 | 0.06803 | 0.02394 | 0.00001 |
| Canada | 0.00001 | 0.00678 | 0.00001 | 0.04064 | 0.01907 | 0.00001 |
| Chile | 0.00001 | 0.00800 | 0.00001 | 0.09601 | 0.03202 | 0.00001 |
| Cyprus | 0.01218 | 0.00001 | 0.00001 | 0.00001 | 0.03698 | 0.00001 |
| Czech Republic | 0.00001 | 0.01147 | 0.00005 | 0.00001 | 0.02096 | 0.00001 |
| Ecuador | 0.00001 | 0.00001 | 0.00001 | 0.14350 | 0.03912 | 0.00001 |
| Estonia | 0.00566 | 0.00703 | 0.00001 | 0.00001 | 0.02300 | 0.00001 |
| Finland | 0.00369 | 0.00837 | 0.00001 | 0.00001 | 0.00001 | 0.01008 |
| France | 0.00001 | 0.00743 | 0.00001 | 0.03286 | 0.00001 | 0.00878 |
| Germany | 0.00001 | 0.00730 | 0.00001 | 0.03227 | 0.00001 | 0.00862 |
| Greece | 0.00001 | 0.00663 | 0.00001 | 0.07245 | 0.02522 | 0.00001 |
| Hungary | 0.00001 | 0.00760 | 0.00001 | 0.08918 | 0.03004 | 0.00001 |
| Iceland | 0.00059 | 0.00868 | 0.00001 | 0.03826 | 0.00001 | 0.01073 |
| Ireland | 0.00607 | 0.00737 | 0.00001 | 0.00001 | 0.02436 | 0.00001 |
| Israel | 0.00691 | 0.00806 | 0.00001 | 0.00001 | 0.02715 | 0.00001 |
| Italy | 0.00001 | 0.00001 | 0.00001 | 0.11379 | 0.00001 | 0.01742 |
| Japan | 0.01035 | 0.00001 | 0.00001 | 0.00001 | 0.03186 | 0.00001 |
| Latvia | 0.00883 | 0.00965 | 0.00001 | 0.00001 | 0.03351 | 0.00001 |
| Malta | 0.00001 | 0.01598 | 0.00007 | 0.00001 | 0.02920 | 0.00001 |
| Mauritius | 0.01053 | 0.00001 | 0.00001 | 0.00001 | 0.03236 | 0.00001 |
| Morocco | 0.01052 | 0.01105 | 0.00001 | 0.00001 | 0.03909 | 0.00001 |
| Netherlands | 0.00001 | 0.00954 | 0.00004 | 0.01949 | 0.02069 | 0.00001 |

| Location | Seat Belt | | Road Safety | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | % Seat Belt Use Rear Seats | Road Density (km/1000 km^2) | Health Expenditure, total (% of GDP) | Number of Fatalities per Million Inhabitants | Fatalities per Million Passenger Cars |
| New Zealand | 0.00331 | 0.00783 | 0.00001 | 0.00001 | 0.00001 | 0.00932 |
| Norway | 0.00224 | 0.00625 | 0.00001 | 0.02938 | 0.02037 | 0.00001 |
| Oman | 0.01051 | 0.00001 | 0.00001 | 0.00001 | 0.03230 | 0.00001 |
| Peru | 0.00890 | 0.00971 | 0.00001 | 0.00001 | 0.03373 | 0.00001 |
| Poland | 0.00793 | 0.00891 | 0.00001 | 0.00001 | 0.03052 | 0.00001 |
| Romania | 0.00978 | 0.01044 | 0.00001 | 0.00001 | 0.03666 | 0.00001 |
| Serbia | 0.00001 | 0.00001 | 0.00001 | 0.09605 | 0.02712 | 0.00001 |
| Spain | 0.00001 | 0.00785 | 0.00001 | 0.05242 | 0.00968 | 0.00620 |
| Sweden | 0.00001 | 0.01062 | 0.00005 | 0.00001 | 0.01940 | 0.00001 |
| Switzerland | 0.00001 | 0.00767 | 0.00001 | 0.04839 | 0.00791 | 0.00655 |
| United Kingdom | 0.00001 | 0.01058 | 0.00005 | 0.00001 | 0.01934 | 0.00001 |
| United States | 0.00001 | 0.00471 | 0.00001 | 0.03952 | 0.01572 | 0.00001 |

Table 13 presents the countries in alphabetical order to show a clearer view of the effects of the additional variable on the efficiency score. With the additional input variable, 28 countries improve their efficiency score, seven countries' scores regress, and one country (Malta) shows no change. With the addition of this fourth variable, the Netherlands, Sweden, and the United Kingdom are now considered efficient countries, as their scores improve to 1.000. The biggest improvements, score wise, can be seen in Estonia, the Czech Republic, and Poland whose score improved from 4.9091 to 3.3638 (difference = 1.5453), from 3.9594 to 2.4809 (difference = 1.4785), and from 5.8985 to 4.4739 (difference = 1.4246), respectively. This can be attributed to a high percentage of seatbelt use in rear seats relative to the other variables under consideration. For example, the rate of seatbelt use in rear seats for the Czech Republic is 80% and the number of fatalities per million inhabitants is 146, one of the highest numbers of fatalities amongst the other countries. So in essence, it has a high rate of seatbelt use in rear seats relative to the number of fatalities per million inhabitants resulting in more optimal weights in the model and an overall higher safety performance level. The countries whose scores show regression actually exhibit an extremely small change compared to the change in the countries whose scores improved. The change is so small that it can be implied that the scores of these countries are not really affected and present no change. This can be attributed to the fact that their percentages of seatbelt use in rear seats is extremely low compared to the rest of the field and therefore has little, or no, effect on the new efficiency scores. Overall, it can be stated that the addition of the fourth input variable improved the efficiency scores of the countries in Analysis 1. If this made a difference in the rankings will be discussed in the following subsection.

**Table 13 – Effects of an additional input variable on the efficiency scores in Analysis 1**

| COUNTRY | SCORE 3 INPUTS | SCORE 4 INPUTS | DIFFERENCE | CHANGE |
|---|---|---|---|---|
| Australia | 2.4320 | 1.2564 | 1.1756 | IMPROVED |
| Austria | 2.2747 | 1.9356 | 0.3391 | IMPROVED |
| Belgium | 2.7856 | 2.4066 | 0.3790 | IMPROVED |
| Canada | 2.4558 | 1.6754 | 0.7804 | IMPROVED |
| Chile | 5.4160 | 4.4014 | 1.0146 | IMPROVED |
| Cyprus | 3.0978 | 3.0980 | -0.0003 | REGRESSED |
| Czech Republic | 3.9594 | 2.4809 | 1.4785 | IMPROVED |
| Ecuador | 5.1209 | 5.1213 | -0.0003 | REGRESSED |
| Estonia | 4.9091 | 3.3638 | 1.5453 | IMPROVED |
| Finland | 2.4561 | 1.5450 | 0.9110 | IMPROVED |
| France | 1.8292 | 1.2732 | 0.5560 | IMPROVED |
| Germany | 1.5967 | 1.0361 | 0.5606 | IMPROVED |
| Greece | 4.1950 | 3.7370 | 0.4581 | IMPROVED |
| Hungary | 4.3593 | 3.6851 | 0.6742 | IMPROVED |
| Iceland | 2.3860 | 1.5527 | 0.8333 | IMPROVED |
| Ireland | 2.9321 | 2.0428 | 0.8893 | IMPROVED |
| Israel | 1.8526 | 1.5070 | 0.3457 | IMPROVED |
| Italy | 2.8342 | 2.8345 | -0.0003 | REGRESSED |
| Japan | 1.6563 | 1.6565 | -0.0001 | REGRESSED |
| Latvia | 6.9139 | 5.9970 | 0.9169 | IMPROVED |
| Malta | 1.0000 | 1.0000 | 0.0000 | NO CHANGE |
| Mauritius | 3.6032 | 3.6036 | -0.0004 | REGRESSED |
| Morocco | 4.9936 | 4.8609 | 0.1327 | IMPROVED |
| Netherlands | 1.3566 | 1.0000 | 0.3566 | IMPROVED |
| New Zealand | 2.8906 | 1.5176 | 1.3730 | IMPROVED |
| Norway | 1.5662 | 1.0087 | 0.5575 | IMPROVED |
| Oman | 10.0793 | 10.0811 | -0.0018 | REGRESSED |
| Peru | 4.4919 | 4.2361 | 0.2558 | IMPROVED |
| Poland | 5.8985 | 4.4739 | 1.4246 | IMPROVED |
| Romania | 4.7374 | 4.6222 | 0.1152 | IMPROVED |
| Serbia | 3.5409 | 3.5415 | -0.0007 | REGRESSED |
| Spain | 2.9492 | 2.0533 | 0.8959 | IMPROVED |
| Sweden | 1.5916 | 1.0000 | 0.5916 | IMPROVED |
| Switzerland | 1.2853 | 1.0000 | 0.2853 | IMPROVED |
| United Kingdom | 1.7499 | 1.0468 | 0.7031 | IMPROVED |
| United States | 2.6169 | 2.2281 | 0.3888 | IMPROVED |

Table 14 presents the efficiency scores of the 24 countries in Analysis 2. In the case of three input variables, Japan, Sweden, Switzerland, and Norway all obtain an efficiency score of 1.000 and are considered to be the best performing countries in the dataset. The addition of a fourth input variable gives the United Kingdom an efficiency score of 1.000, which adds it to the list of best performing countries. The addition of the fifth input variable does not provide any other countries with an optimal score of one but this does not mean it has no effect on the other scores.

**Table 14 – Efficiency scores for Analysis 2**

| COUNTRY | SCORE 3 INPUTS |
|---|---|
| Japan | 1.0000 |
| Sweden | 1.0000 |
| Switzerland | 1.0000 |
| Norway | 1.0000 |
| United Kingdom | 1.0899 |
| Israel | 1.1381 |
| Belgium | 1.1586 |
| France | 1.3205 |
| Australia | 1.3613 |
| Finland | 1.5093 |
| Iceland | 1.5360 |
| New Zealand | 1.5995 |
| Austria | 1.6675 |
| Ireland | 1.8000 |
| Cyprus | 1.8805 |
| United States | 1.9493 |
| Mauritius | 2.2083 |
| Hungary | 2.9470 |
| Estonia | 3.0080 |
| Morocco | 3.1255 |
| Poland | 3.6543 |
| Ecuador | 4.1243 |
| Chile | 4.3595 |
| Oman | 6.1853 |

| COUNTRY | SCORE 4 INPUTS |
|---|---|
| Norway | 1.0000 |
| United Kingdom | 1.0000 |
| Japan | 1.0000 |
| Sweden | 1.0000 |
| Switzerland | 1.0000 |
| Belgium | 1.0713 |
| Israel | 1.1386 |
| France | 1.2510 |
| Australia | 1.2564 |
| New Zealand | 1.5031 |
| Iceland | 1.5068 |
| Finland | 1.5093 |
| Austria | 1.6678 |
| Ireland | 1.8000 |
| Cyprus | 1.8815 |
| United States | 1.9496 |
| Mauritius | 2.2100 |
| Hungary | 2.7141 |
| Estonia | 3.0081 |
| Morocco | 3.1271 |
| Poland | 3.6546 |
| Ecuador | 4.1255 |
| Chile | 4.2738 |
| Oman | 6.1906 |

| COUNTRY | SCORE 5 INPUTS |
|---|---|
| United Kingdom | 1.0000 |
| Japan | 1.0000 |
| Sweden | 1.0000 |
| Switzerland | 1.0000 |
| Norway | 1.0000 |
| Belgium | 1.0721 |
| Israel | 1.0934 |
| France | 1.2439 |
| Australia | 1.2472 |
| New Zealand | 1.4841 |
| Finland | 1.5013 |
| Iceland | 1.5075 |
| Austria | 1.6615 |
| Ireland | 1.7026 |
| Cyprus | 1.8783 |
| United States | 1.9512 |
| Mauritius | 2.1451 |
| Hungary | 2.7152 |
| Estonia | 3.0084 |
| Morocco | 3.1272 |
| Poland | 3.6206 |
| Ecuador | 4.1276 |
| Chile | 4.2755 |
| Oman | 6.1932 |

Table 15, Table 16, and Table 17 present the country specific weights of each RSPI for the models in Analysis 2. Australia will be used as an illustration. As can be seen in Table 15, for 3 input variables, Australia received its highest weight (0.01030) in the percentage of seat belt use in front seats category. However, for 4 input variables (Table 16) and 5 input variables (Table 17), the percentage of seat belt use in rear seats category received the highest weight, 0.01085 and 0.01051 respectively. Iceland, on the other hand, received the highest weight in the first category, percentage of seat belt use in front seats, for all three sub-analyses. For 3 input variables, category one received a weight of 0.01135.; for 4 input variables, category one received a weight of 0.00867; and for 5 input variables, category one received a weight of 0.00864. As apparent in all three tables, most countries in Analysis 2 performed well in the first category, percentage of seat belt use in front seats, as they received the highest weighting in this category.

Since the DEA weighting method finds the best possible combination of weights for each country, it should be noted that a country that appears in both Analysis 1 and Analysis 2 will obtain the same weights regardless of the other countries in the dataset. For example, the weights for Australia for 3 and 4 input variables in Analysis 1 are the same as the weights for 3 and 4 input variables in Analysis 2. This is evident when the weights in Table 11 and Table 12 are compared with Table 15 and Table 16.

**Table 15 – Country specific weights: 3 inputs (Analysis 2)**

| Location | Seat Belt | Road Safety | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | Road Density (km/1000 km^2) | Health Expenditure, total (% of GDP) | Number of Fatalities per million Inhabitants | Fatalities per Million Passenger Cars |
| Australia | 0.01030 | 0.00001 | 0.00001 | 0.00001 | 0.00965 |
| Austria | 0.01109 | 0.00001 | 0.00001 | 0.01159 | 0.00432 |
| Belgium | 0.00001 | 0.00020 | 0.00001 | 0.00001 | 0.00549 |
| Chile | 0.00001 | 0.00001 | 0.14470 | 0.03171 | 0.00001 |
| Cyprus | 0.01195 | 0.00002 | 0.00001 | 0.01477 | 0.00370 |
| Ecuador | 0.00001 | 0.00001 | 0.14351 | 0.03145 | 0.00001 |
| Estonia | 0.01088 | 0.00002 | 0.00001 | 0.02056 | 0.00001 |
| Finland | 0.01121 | 0.00001 | 0.00001 | 0.01169 | 0.00437 |
| France | 0.00831 | 0.00002 | 0.01396 | 0.01822 | 0.00001 |
| Hungary | 0.00001 | 0.00018 | 0.08078 | 0.02402 | 0.00001 |
| Iceland | 0.01135 | 0.00001 | 0.00001 | 0.00001 | 0.01062 |
| Ireland | 0.01135 | 0.00002 | 0.00001 | 0.02146 | 0.00001 |
| Israel | 0.01087 | 0.00001 | 0.00001 | 0.02049 | 0.00001 |
| Japan | 0.01017 | 0.00002 | 0.00001 | 0.01922 | 0.00001 |
| Mauritius | 0.01047 | 0.00002 | 0.00001 | 0.01979 | 0.00001 |
| Morocco | 0.01332 | 0.00001 | 0.00001 | 0.02507 | 0.00001 |
| New Zealand | 0.01049 | 0.00001 | 0.00001 | 0.00001 | 0.00983 |
| Norway | 0.01071 | 0.00001 | 0.00001 | 0.02019 | 0.00001 |
| Oman | 0.01051 | 0.00001 | 0.00001 | 0.01979 | 0.00001 |
| Poland | 0.01318 | 0.00002 | 0.00001 | 0.02493 | 0.00001 |
| Sweden | 0.01021 | 0.00002 | 0.00001 | 0.01263 | 0.00316 |
| Switzerland | 0.00930 | 0.00002 | 0.01562 | 0.02039 | 0.00001 |
| United Kingdom | 0.01058 | 0.00002 | 0.00001 | 0.01308 | 0.00327 |
| United States | 0.00001 | 0.00001 | 0.06182 | 0.01375 | 0.00001 |

**Table 16 – Country specific weights: 4 inputs (Analysis 2)**

| Location | Seat Belt | | Road Safety | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | % Seat Belt Use Rear Seats | Road Density (km/1000 km^2) | Health Expenditure, total (% of GDP) | Number of Fatalities per million Inhabitants | Fatalities per Million Passenger Cars |
| Australia | 0.00001 | 0.01085 | 0.00001 | 0.00001 | 0.00001 | 0.00891 |
| Austria | 0.01109 | 0.00001 | 0.00001 | 0.00001 | 0.01155 | 0.00433 |
| Belgium | 0.00001 | 0.00287 | 0.00017 | 0.00001 | 0.00001 | 0.00507 |
| Chile | 0.00001 | 0.00842 | 0.00001 | 0.09344 | 0.03109 | 0.00001 |
| Cyprus | 0.01194 | 0.00001 | 0.00002 | 0.00001 | 0.01479 | 0.00369 |
| Ecuador | 0.00001 | 0.00001 | 0.00001 | 0.14350 | 0.03146 | 0.00001 |
| Estonia | 0.01086 | 0.00001 | 0.00002 | 0.00001 | 0.02057 | 0.00001 |
| Finland | 0.01120 | 0.00001 | 0.00001 | 0.00001 | 0.01166 | 0.00439 |
| France | 0.00001 | 0.00855 | 0.00011 | 0.00945 | 0.00001 | 0.00863 |
| Hungary | 0.00001 | 0.00612 | 0.00028 | 0.02057 | 0.02212 | 0.00001 |
| Iceland | 0.00867 | 0.00346 | 0.00001 | 0.00001 | 0.00001 | 0.01042 |
| Ireland | 0.01134 | 0.00001 | 0.00002 | 0.00001 | 0.02146 | 0.00001 |
| Israel | 0.01087 | 0.00001 | 0.00001 | 0.00001 | 0.02050 | 0.00001 |
| Japan | 0.01015 | 0.00001 | 0.00002 | 0.00001 | 0.01922 | 0.00001 |
| Mauritius | 0.01046 | 0.00001 | 0.00002 | 0.00001 | 0.01981 | 0.00001 |
| Morocco | 0.01331 | 0.00001 | 0.00001 | 0.00001 | 0.02508 | 0.00001 |
| New Zealand | 0.00763 | 0.00312 | 0.00001 | 0.00001 | 0.00001 | 0.00923 |
| Norway | 0.00882 | 0.00001 | 0.00001 | 0.02015 | 0.02019 | 0.00001 |
| Oman | 0.01051 | 0.00001 | 0.00001 | 0.00001 | 0.01981 | 0.00001 |
| Poland | 0.01317 | 0.00001 | 0.00002 | 0.00001 | 0.02493 | 0.00001 |
| Sweden | 0.00001 | 0.00663 | 0.00011 | 0.03319 | 0.01940 | 0.00001 |
| Switzerland | 0.00001 | 0.00564 | 0.00026 | 0.01896 | 0.02039 | 0.00001 |
| United Kingdom | 0.00001 | 0.00631 | 0.00011 | 0.03160 | 0.01847 | 0.00001 |
| United States | 0.00001 | 0.00001 | 0.00001 | 0.06177 | 0.01375 | 0.00001 |

**Table 17 – Country specific weights: 5 inputs (Analysis 2)**

| Location | Seat Belt | | Road Safety | | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | % Seat Belt Use Rear Seats | Road Density (km/1000 km^2) | Roads, paved (% of total roads) | Health Expenditure, total (% of GDP) | Number of Fatalities per million Inhabitants | Fatalities per Million Passenger Cars |
| Australia | 0.00001 | 0.01051 | 0.00001 | 0.00073 | 0.00001 | 0.00001 | 0.00884 |
| Austria | 0.00888 | 0.00001 | 0.00001 | 0.00196 | 0.00001 | 0.01994 | 0.00001 |
| Belgium | 0.00001 | 0.00286 | 0.00017 | 0.00001 | 0.00001 | 0.00001 | 0.00508 |
| Chile | 0.00001 | 0.00844 | 0.00001 | 0.00001 | 0.09331 | 0.03110 | 0.00001 |
| Cyprus | 0.01188 | 0.00001 | 0.00002 | 0.00017 | 0.00001 | 0.01618 | 0.00301 |
| Ecuador | 0.00001 | 0.00001 | 0.00001 | 0.00001 | 0.14347 | 0.03148 | 0.00001 |
| Estonia | 0.01086 | 0.00001 | 0.00002 | 0.00001 | 0.00001 | 0.02057 | 0.00001 |
| Finland | 0.00624 | 0.00512 | 0.00001 | 0.00050 | 0.00001 | 0.00001 | 0.00980 |
| France | 0.00001 | 0.00871 | 0.00003 | 0.00088 | 0.01208 | 0.00001 | 0.00858 |
| Hungary | 0.00001 | 0.00612 | 0.00028 | 0.00001 | 0.02053 | 0.02213 | 0.00001 |
| Iceland | 0.00864 | 0.00350 | 0.00001 | 0.00001 | 0.00001 | 0.00001 | 0.01042 |
| Ireland | 0.00001 | 0.00397 | 0.00001 | 0.00735 | 0.00001 | 0.02030 | 0.00001 |
| Israel | 0.00878 | 0.00001 | 0.00001 | 0.00193 | 0.00001 | 0.01969 | 0.00001 |
| Japan | 0.00001 | 0.00620 | 0.00029 | 0.00001 | 0.00001 | 0.01922 | 0.00001 |
| Mauritius | 0.00858 | 0.00001 | 0.00001 | 0.00187 | 0.00001 | 0.01922 | 0.00001 |
| Morocco | 0.01330 | 0.00001 | 0.00001 | 0.00001 | 0.00001 | 0.02508 | 0.00001 |
| New Zealand | 0.00573 | 0.00484 | 0.00001 | 0.00048 | 0.00001 | 0.00001 | 0.00912 |
| Norway | 0.00765 | 0.00249 | 0.00006 | 0.00073 | 0.00001 | 0.02019 | 0.00001 |
| Oman | 0.01050 | 0.00001 | 0.00001 | 0.00001 | 0.00001 | 0.01982 | 0.00001 |
| Poland | 0.01136 | 0.00001 | 0.00002 | 0.00198 | 0.00001 | 0.02470 | 0.00001 |
| Sweden | 0.00735 | 0.00240 | 0.00006 | 0.00070 | 0.00001 | 0.01940 | 0.00001 |
| Switzerland | 0.00001 | 0.00399 | 0.00001 | 0.00738 | 0.00001 | 0.02039 | 0.00001 |
| United Kingdom | 0.00700 | 0.00228 | 0.00006 | 0.00067 | 0.00001 | 0.01847 | 0.00001 |
| United States | 0.00001 | 0.00001 | 0.00001 | 0.00001 | 0.06173 | 0.01376 | 0.00001 |

In Table 18, the countries are alphabetically organized to present a clearer view of the effect of the additional variables on the efficiency scores. Compared to Analysis 1, the addition of a fourth and fifth input variable has a much smaller effect on efficiency scores – value wise. Table 18 shows that the addition of a fourth input variable results in a score improvement for eight countries, a regression in 10 countries, and no change in the remaining six countries (three of which had already obtained a score of 1.000 prior to the addition of the fourth input variable). The addition of a fifth input variable results in a score improvement for 10 countries, a regression in nine countries, and no change in the remaining five countries (all of which had already obtained a score of 1.000 prior to the addition of the fifth input variable). Finally, results indicate that more than half of the countries show an improvement when comparing the scores of three and five input variables (addition of two variables), and five countries show a regression. Yet again, the countries that show no change are those who had already obtained a score of 1.000 prior to the addition of the variables. Similar to Analysis 1, the countries whose scores regress do so very little relative to the change in the countries whose scores improved. In this sub-analysis, the addition of two extra input variables has a positive impact on the efficiency scores as one additional country obtains an optimal efficiency score of 1.000 and many others improve their score. The biggest improvements are seen in Hungary, New Zealand, and Australia whose score improved from 2.9470 to 2.7152 (difference = 0.2319), from 1.5995 to 1.4841 (difference = 0.1154), and from 1.3616 to 1.2472 (difference = 0.1141), respectively. These changes can be attributed to the fact that relative to the variables already under consideration, these countries perform well in the additional variable categories – the percentage of seatbelt use in rear seats and the percentage of paved roads – and therefore receive a higher weighting in the model. Section 3.3.2 will examine if these improvements or regressions make a difference in the ranking.

**Table 18 – Effects of an additional input variable on the efficiency scores in Analysis 2**

| COUNTRY | SCORE 3 INPUTS | SCORE 4 INPUTS | SCORE 5 INPUTS | DIFFERENCE 3-4 | CHANGE | DIFFERENCE 4-5 | CHANGE | DIFFERENCE 3-5 | CHANGE |
|---|---|---|---|---|---|---|---|---|---|
| Australia | 1.3613 | 1.2564 | 1.2472 | 0.1049 | IMPROVED | 0.0092 | IMPROVED | 0.1141 | IMPROVED |
| Austria | 1.6675 | 1.6678 | 1.6615 | -0.0003 | REGRESSED | 0.0063 | IMPROVED | 0.0059 | IMPROVED |
| Belgium | 1.1586 | 1.0713 | 1.0721 | 0.0873 | IMPROVED | -0.0008 | REGRESSED | 0.0865 | IMPROVED |
| Chile | 4.3595 | 4.2738 | 4.2755 | 0.0857 | IMPROVED | -0.0017 | REGRESSED | 0.0840 | IMPROVED |
| Cyprus | 1.8805 | 1.8815 | 1.8783 | -0.0010 | REGRESSED | 0.0032 | IMPROVED | 0.0022 | IMPROVED |
| Ecuador | 4.1243 | 4.1255 | 4.1276 | -0.0012 | REGRESSED | -0.0021 | REGRESSED | -0.0033 | REGRESSED |
| Estonia | 3.0080 | 3.0081 | 3.0084 | -0.0001 | REGRESSED | -0.0003 | REGRESSED | -0.0004 | REGRESSED |
| Finland | 1.5093 | 1.5093 | 1.5013 | 0.0000 | NO CHANGE | 0.0080 | IMPROVED | 0.0079 | IMPROVED |
| France | 1.3205 | 1.2510 | 1.2439 | 0.0695 | IMPROVED | 0.0071 | IMPROVED | 0.0766 | IMPROVED |
| Hungary | 2.9470 | 2.7141 | 2.7152 | 0.2330 | IMPROVED | -0.0011 | REGRESSED | 0.2319 | IMPROVED |
| Iceland | 1.5360 | 1.5068 | 1.5075 | 0.0292 | IMPROVED | -0.0007 | REGRESSED | 0.0285 | IMPROVED |
| Ireland | 1.8000 | 1.8000 | 1.7026 | 0.0000 | NO CHANGE | 0.0974 | IMPROVED | 0.0974 | IMPROVED |
| Israel | 1.1381 | 1.1386 | 1.0934 | -0.0005 | REGRESSED | 0.0452 | IMPROVED | 0.0447 | IMPROVED |
| Japan | 1.0000 | 1.0000 | 1.0000 | 0.0000 | NO CHANGE | 0.0000 | NO CHANGE | 0.0000 | NO CHANGE |
| Mauritius | 2.2083 | 2.2100 | 2.1451 | -0.0017 | REGRESSED | 0.0649 | IMPROVED | 0.0633 | IMPROVED |
| Morocco | 3.1255 | 3.1271 | 3.1272 | -0.0015 | REGRESSED | -0.0001 | REGRESSED | -0.0016 | REGRESSED |
| New Zealand | 1.5995 | 1.5031 | 1.4841 | 0.0964 | IMPROVED | 0.0190 | IMPROVED | 0.1154 | IMPROVED |
| Norway | 1.0000 | 1.0000 | 1.0000 | 0.0000 | NO CHANGE | 0.0000 | NO CHANGE | 0.0000 | NO CHANGE |
| Oman | 6.1853 | 6.1906 | 6.1932 | -0.0053 | REGRESSED | -0.0025 | REGRESSED | -0.0078 | REGRESSED |
| Poland | 3.6543 | 3.6546 | 3.6206 | -0.0003 | REGRESSED | 0.0340 | IMPROVED | 0.0337 | IMPROVED |
| Sweden | 1.0000 | 1.0000 | 1.0000 | 0.0000 | NO CHANGE | 0.0000 | NO CHANGE | 0.0000 | NO CHANGE |
| Switzerland | 1.0000 | 1.0000 | 1.0000 | 0.0000 | NO CHANGE | 0.0000 | NO CHANGE | 0.0000 | NO CHANGE |
| United Kingdom | 1.0899 | 1.0000 | 1.0000 | 0.0899 | IMPROVED | 0.0000 | NO CHANGE | 0.0899 | IMPROVED |
| United States | 1.9493 | 1.9496 | 1.9512 | -0.0003 | REGRESSED | -0.0016 | REGRESSED | -0.0020 | REGRESSED |

### *3.3.2 Rankings*

In addition to ranking the countries, this section will examine whether adding additional input variables has any effect on these rankings. Using the calculated efficiency scores from Section 3.3.1, the countries can be ranked accordingly. The countries' efficiency scores are arranged in ascending order with a score of one being the most efficient or best performing and anything greater than one being inefficient or underperforming. Once sorted, they are given a ranking from 1 to 36 (Analysis 1) or 1 to 24 (Analysis 2). It should be noted that a country's rank is relative to the other countries in its dataset. For this reason, the rankings for Analysis 1 cannot be compared with the rankings of Analysis 2 as both contain a different number of countries and a different number of input variables.

Table 19 shows the ranking for Analysis 1 in ascending order for its 36 countries whereas Table 20 displays the ranking results in alphabetical order. This is to allow for easier interpretation of the ranking differences. Of the 36 countries, 13 improved their standing, seven maintained their standing, and 16 countries declined in the rankings when changing the analysis from three input variables to four input variables. As was shown in Section 3.3.1, most countries saw a positive improvement in their efficiency scores, yet not all those countries improved or maintained their ranking. For example, Austria, Belgium, and Canada all improved their efficiency score, yet they fell in the rankings. This can be linked to the fact that some countries showed a bigger improvement in their efficiency scores than others, therefore positioning them higher in the overall rankings. It was mentioned in Section 3.3.1 that Estonia had the greatest improvement in its efficiency score and it is seen here that it improved its standing by 6 places, going from $30^{th}$ place to $24^{th}$. The country with the greatest improvement in standings, however, is New Zealand, which jumped up from $19^{th}$ place into $11^{th}$ place. Japan, on the other hand, shows the biggest regression in ranking as it falls from $7^{th}$ place into $14^{th}$ place. It is interesting to note that Japan's efficiency score actually did not change with the addition of a fourth variable, yet it fell seven places in the rankings. This, too, is linked to the fact that other countries showed greater improvement in their efficiency scores, which lead to them earning a higher ranking.

**Table 19 – Ranking for Analysis 1**

| COUNTRY | RANK 3 INPUTS | COUNTRY | RANK 4 INPUTS |
|---|---|---|---|
| Malta | 1 | Malta | 1 |
| Switzerland | 2 | Netherlands | 1 |
| Netherlands | 3 | Sweden | 1 |
| Norway | 4 | Switzerland | 1 |
| Sweden | 5 | Norway | 5 |
| Germany | 6 | Germany | 6 |
| Japan | 7 | United Kingdom | 7 |
| United Kingdom | 8 | Australia | 8 |
| France | 9 | France | 9 |
| Israel | 10 | Israel | 10 |
| Austria | 11 | New Zealand | 11 |
| Iceland | 12 | Finland | 12 |
| Australia | 13 | Iceland | 13 |
| Canada | 14 | Japan | 14 |
| Finland | 15 | Canada | 15 |
| United States | 16 | Austria | 16 |
| Belgium | 17 | Ireland | 17 |
| Italy | 18 | Spain | 18 |
| New Zealand | 19 | United States | 19 |
| Ireland | 20 | Belgium | 20 |
| Spain | 21 | Czech Republic | 21 |
| Cyprus | 22 | Italy | 22 |
| Serbia | 23 | Cyprus | 23 |
| Mauritius | 24 | Estonia | 24 |
| Czech Republic | 25 | Serbia | 25 |
| Greece | 26 | Mauritius | 26 |
| Hungary | 27 | Hungary | 27 |
| Peru | 28 | Greece | 28 |
| Romania | 29 | Peru | 29 |
| Estonia | 30 | Chile | 30 |
| Morocco | 31 | Poland | 31 |
| Ecuador | 32 | Romania | 32 |
| Chile | 33 | Morocco | 33 |
| Poland | 34 | Ecuador | 34 |
| Latvia | 35 | Latvia | 35 |
| Oman | 36 | Oman | 36 |

**Table 20 – Comparison between the two rankings for Analysis 1**

| COUNTRY | RANK 3 INPUTS | RANK 4 INPUTS | DIFFERENCE | CHANGE |
|---|---|---|---|---|
| Australia | 13 | 8 | 5 | IMPROVED |
| Austria | 11 | 16 | -5 | REGRESSED |
| Belgium | 17 | 20 | -3 | REGRESSED |
| Canada | 14 | 15 | -1 | REGRESSED |
| Chile | 33 | 30 | 3 | IMPROVED |
| Cyprus | 22 | 23 | -1 | REGRESSED |
| Czech Republic | 25 | 21 | 4 | IMPROVED |
| Ecuador | 32 | 34 | -2 | REGRESSED |
| Estonia | 30 | 24 | 6 | IMPROVED |
| Finland | 15 | 12 | 3 | IMPROVED |
| France | 9 | 9 | 0 | NO CHANGE |
| Germany | 6 | 6 | 0 | NO CHANGE |
| Greece | 26 | 28 | -2 | REGRESSED |
| Hungary | 27 | 27 | 0 | NO CHANGE |
| Iceland | 12 | 13 | -1 | REGRESSED |
| Ireland | 20 | 17 | 3 | IMPROVED |
| Israel | 10 | 10 | 0 | NO CHANGE |
| Italy | 18 | 22 | -4 | REGRESSED |
| Japan | 7 | 14 | -7 | REGRESSED |
| Latvia | 35 | 35 | 0 | NO CHANGE |
| Malta | 1 | 1 | 0 | NO CHANGE |
| Mauritius | 24 | 26 | -2 | REGRESSED |
| Morocco | 31 | 33 | -2 | REGRESSED |
| Netherlands | 3 | 1 | 2 | IMPROVED |
| New Zealand | 19 | 11 | 8 | IMPROVED |
| Norway | 4 | 5 | -1 | REGRESSED |
| Oman | 36 | 36 | 0 | NO CHANGE |
| Peru | 28 | 29 | -1 | REGRESSED |
| Poland | 34 | 31 | 3 | IMPROVED |
| Romania | 29 | 32 | -3 | REGRESSED |
| Serbia | 23 | 25 | -2 | REGRESSED |
| Spain | 21 | 18 | 3 | IMPROVED |
| Sweden | 5 | 1 | 4 | IMPROVED |
| Switzerland | 2 | 1 | 1 | IMPROVED |
| United Kingdom | 8 | 7 | 1 | IMPROVED |
| United States | 16 | 19 | -3 | REGRESSED |

Table 21 shows the ranking for Analysis 2 in ascending order for its 24 countries and Table 22 displays the ranking results in alphabetical order. In the case of Analysis 2, and as shown in Table 22, the rankings are more consistent and actually show very little change when shifting the analysis from three input variables to four input variables to then five input variables. With the addition of two extra input variables (difference 3-5 column), all but six countries maintained their original ranking. For the countries whose ranking did change, it did not change by more than one or two ranks (in either direction) except for the United Kingdom, which jumped 4 places in the rankings going from 5$^{th}$ place to 1$^{st}$ place. It looks as though adding more input variables to a smaller group of countries does not result in a change of the rankings. In turn, it can be concluded, in the case of Analysis 2, that the additions of the extra variables made little to no difference in the rankings despite the fact that most of the countries improved their efficiency score as shown in the previous subsection.

**Table 21 – Ranking for Analysis 2**

| COUNTRY | RANK 3 INPUTS |
|---|---|
| Japan | 1 |
| Sweden | 1 |
| Switzerland | 1 |
| Norway | 1 |
| United Kingdom | 5 |
| Israel | 6 |
| Belgium | 7 |
| France | 8 |
| Australia | 9 |
| Finland | 10 |
| Iceland | 11 |
| New Zealand | 12 |
| Austria | 13 |
| Ireland | 14 |
| Cyprus | 15 |
| United States | 16 |
| Mauritius | 17 |
| Hungary | 18 |
| Estonia | 19 |
| Morocco | 20 |
| Poland | 21 |
| Ecuador | 22 |
| Chile | 23 |
| Oman | 24 |

| COUNTRY | RANK 4 INPUTS |
|---|---|
| Norway | 1 |
| United Kingdom | 1 |
| Japan | 1 |
| Sweden | 1 |
| Switzerland | 1 |
| Belgium | 6 |
| Israel | 7 |
| France | 8 |
| Australia | 9 |
| New Zealand | 10 |
| Iceland | 11 |
| Finland | 12 |
| Austria | 13 |
| Ireland | 14 |
| Cyprus | 15 |
| United States | 16 |
| Mauritius | 17 |
| Hungary | 18 |
| Estonia | 19 |
| Morocco | 20 |
| Poland | 21 |
| Ecuador | 22 |
| Chile | 23 |
| Oman | 24 |

| COUNTRY | RANK 5 INPUTS |
|---|---|
| United Kingdom | 1 |
| Japan | 1 |
| Sweden | 1 |
| Switzerland | 1 |
| Norway | 1 |
| Belgium | 6 |
| Israel | 7 |
| France | 8 |
| Australia | 9 |
| New Zealand | 10 |
| Finland | 11 |
| Iceland | 12 |
| Austria | 13 |
| Ireland | 14 |
| Cyprus | 15 |
| United States | 16 |
| Mauritius | 17 |
| Hungary | 18 |
| Estonia | 19 |
| Morocco | 20 |
| Poland | 21 |
| Ecuador | 22 |
| Chile | 23 |
| Oman | 24 |

**Table 22 – Comparison between the three rankings for Analysis 2**

| COUNTRY | RANK 3 INPUTS | RANK 4 INPUTS | RANK 5 INPUTS | DIFFERENCE 3-4 | CHANGE | DIFFERENCE 4-5 | CHANGE | DIFFERENCE 3-5 | CHANGE |
|---|---|---|---|---|---|---|---|---|---|
| Australia | 9 | 9 | 9 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Austria | 13 | 13 | 13 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Belgium | 7 | 6 | 6 | 1 | IMPROVED | 0 | NO CHANGE | 1 | IMPROVED |
| Chile | 23 | 23 | 23 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Cyprus | 15 | 15 | 15 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Ecuador | 22 | 22 | 22 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Estonia | 19 | 19 | 19 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Finland | 10 | 12 | 11 | -2 | REGRESSED | 1 | IMPROVED | -1 | REGRESSED |
| France | 8 | 8 | 8 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Hungary | 18 | 18 | 18 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Iceland | 11 | 11 | 12 | 0 | NO CHANGE | -1 | REGRESSED | -1 | REGRESSED |
| Ireland | 14 | 14 | 14 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Israel | 6 | 7 | 7 | -1 | REGRESSED | 0 | NO CHANGE | -1 | REGRESSED |
| Japan | 1 | 1 | 1 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Mauritius | 17 | 17 | 17 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Morocco | 20 | 20 | 20 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| New Zealand | 12 | 10 | 10 | 2 | IMPROVED | 0 | NO CHANGE | 2 | IMPROVED |
| Norway | 1 | 1 | 1 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Oman | 24 | 24 | 24 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Poland | 21 | 21 | 21 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Sweden | 1 | 1 | 1 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| Switzerland | 1 | 1 | 1 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |
| United Kingdom | 5 | 1 | 1 | 4 | IMPROVED | 0 | NO CHANGE | 4 | IMPROVED |
| United States | 16 | 16 | 16 | 0 | NO CHANGE | 0 | NO CHANGE | 0 | NO CHANGE |

# 4. Accident Prediction Modeling

The knowledge that research to investigate planning-level safety forecasting on a global scale is relatively limited is the driver behind this chapter. The development of analytical models such as accident prediction models allow transportation planners and transportation agencies to forecast road safety levels by predicting the number of fatalities on a long-term basis. It also allows them to find ways of reducing the severity of the accidents as well as analyzing the potential benefits of proposed remedial actions. The objective of this chapter is to develop a series of accident prediction models on a global scale using road safety performance indicators. The predicted number of fatalities are calculated for each country and compared to the number of observed fatalities by calculating the difference. This difference shows how a country actually performs compared to what is normal (predicted) and which countries have the highest potential for improvement.

## 4.1 Modeling Approach and Development

Two options are available for estimating model parameters after reviewing previous work: the traditional linear regression approach and the generalized linear regression approach. The main difference between the two methods is that the traditional linear regression approach assumes a normal distribution error structure while the generalized linear regression approach assumes a non-normal error structure such as Poisson or negative binomial. Several researchers (Hauer et al., 1988; Sayed & Rodriguez, 1999; Hadayeghi et al., 2003; Ladrón de Guevara et al., 2004) have shown that traditional linear modeling should not used to develop accident prediction models. This is explained by the fact that since road accidents are rare and random events, as well as discrete and nonnegative, it is not appropriate to assume that the data is normally distributed. These studies have instead shown that it is more appropriate to assume Poisson or negative binomial distributions for accident data and to estimate model parameters through generalized linear regression. A generalized linear model is simply an extension of the traditional linear model that overcomes the shortcomings of the traditional linear model when applied to modeling accidents.

A generalized linear model has two common error structures: Poisson and negative binomial. There are advantages and disadvantages to using either structure. An advantage of the Poisson error structure is the simplicity of the calculations as it restricts the mean and variance to be equal ($E[y] = Var[y]$). This, however, is also a disadvantage as accident data is likely to be overdispersed ($E[y] < Var[y]$). The overdispersion of accident data was shown by Miaou (1994). The negative binomial error structure resolves this problem and is therefore more appropriate (Miaou, 1994; Sayed & Rodriguez, 1999; Hadayeghi et al., 2003; Ladrón de Guevara et al., 2004).

The theoretical background of the Poisson regression model and the negative binomial regression model will now be discussed. Let Y be a random variable representing the accident frequency at a given location during a specific time period and let y be the actual observation of Y during that period. Using $\Lambda$ to denote the mean of Y and letting

Λ = λ, the Poisson regression model has the following form (Miaou, 1994; Sawalha & Sayed, 2006):

$$P(Y = y|\Lambda = \lambda) = \frac{\lambda^y e^{-\lambda}}{y!} \tag{4a}$$

$$E(Y|\ \Lambda = \lambda) = \lambda \tag{4b}$$

$$Var(Y|\Lambda = \lambda) = \lambda \tag{4c}$$

When using the Poisson regression model to evaluate the accident data, the overdispersion of the data will result in the underestimation of the variance of the estimated parameters and the estimated coefficients tend to be biased (Miaou, 1994). The use of the negative binomial error structure resolves this problem. The negative binomial regression model has the following form (Miaou, 1994):

$$P(Y = y) = \frac{\Gamma\left(y + \frac{1}{\alpha}\right)}{\Gamma(y+1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{1}{1+\alpha\lambda}\right)^{\frac{1}{\alpha}} \left(\frac{\alpha\lambda}{1+\alpha\lambda}\right)^{y} \tag{5a}$$

$$E(Y) = \lambda \tag{5b}$$

$$Var(Y) = \lambda + \ \alpha \cdot \lambda^2 \tag{5c}$$

where α is the dispersion parameter (α ≥ 0).

Equation (5c) can also be written as follows:

$$Var(Y) = E(Y)[1 + \alpha E(Y)]^2 = E[Y] + \alpha \cdot E[Y]^2 \tag{6}$$

where E is the estimate of the mean accident frequency (Hadayeghi et al., 2003).

With the aforementioned theoretical background, and so as to account for the overdispersion of the data, the accident prediction models in this thesis will be developed using the generalized linear regression approach with a negative binomial error structure. The following model form will be used in this thesis:

$$E(Y) = a_o \cdot Z^{b_0} \cdot \exp\left(\sum_{i=1}^{n} b_i X_i\right) \tag{7}$$

where E(Y) is the predicted number of fatal accidents; Z is the exposure variable; $a_o$, $b_0$, and $b_i$ are the model parameters; and $X_i$ are the explanatory variables (Hadayeghi et al., 2003; Lovegrove & Sayed, 2006).

As discussed in the literature review, deciding what explanatory variables to use in the model can be challenging. A technique offered by Sawalha & Sayed (2006) is to construct the models by adding one variable at a time and seeing how these variables affect the model with regards to goodness-of-fit and the significance level of the variables. This technique starts off with a simple model, also called a base model, that only considers the exposure variable as in equation (8).

$$E(Y) = a_o \cdot Z^{b_0} \tag{8}$$

where E(Y) is the predicted number of fatal accidents; Z is the exposure variable; and $a_o$ and $b_0$ are the model parameters. Once this base model is developed, explanatory variables can be added one at a time.

Several criteria are used to determine whether or not to keep the variables in the model (Hadayeghi et al., 2003; Ladrón de Guevara et al., 2004; Lovegrove & Sayed, 2006). The first criterion one should look at is the variables' ρ-values. The ρ-values of the variable's estimated coefficient should be significant at the 5% or 10% level, indicating a 95% or 90% confidence level, respectively.

Secondly, the addition of an explanatory variable should improve the goodness-of-fit of the model. The goodness-of-fit of the model can be evaluated using two measures: the Pearson $\chi^2$ value and the scaled deviance (McCullagh & Nelder, 1989). The Pearson $\chi^2$ is defined as follows:

$$Pearson\ \chi^2 = \sum_{i=1}^{n} \frac{[y_i - \hat{E}(Y)]^2}{var(y_i)} \tag{9}$$

where $y_i$ is the observed number of fatal accidents in zone i; $\hat{E}(Y_i)$ is the predicted number of fatal accidents for zone i as obtained from the prediction model; and $var(y_i)$ is the variance of the observed accidents. The scaled deviance (SD) is "the likelihood ratio test statistic, measuring twice the difference between the maximized logarithm-likelihoods of the studied model and those of the full or saturated model" (Lovegrove & Sayed, 2006, p. 613). If the error structure follows a negative binomial distribution, the SD is determined as follows:

$$SD = 2\sum_{i=1}^{n} \left\{ y_i \ln\left[\frac{y_i}{\hat{E}(Y_i)}\right] - (y_i + \kappa) \ln\left[\frac{y_i + \kappa}{\hat{E}(Y_i) + \kappa}\right] \right\} \tag{10}$$

where κ is the shape parameter. Both the Pearson $\chi^2$ and the SD have $\chi^2$ distributions for normal theory linear models, but they are asymptotically $\chi^2$ distributed with n – p degrees of freedom (DOF) for other distributions of the exponential family (Sawalha & Sayed, 2003). Accordingly, the Pearson $\chi^2$ and the SD values can be compared with the value from the $\chi^2$ distribution table for the same DOF and the respective confidence level (i.e., 90% or 95% confidence interval). These values must be lower than the $\chi^2$ distribution value found in the table in order for the model to be considered a good fit. Another way these values can be evaluated is by comparing them directly with the DOFs. A model is considered to have a good fit if the ratio of Pearson $\chi^2$ to DOF is close to one. The same is true for the ratio of SD to DOF. The second evaluation method is the one used in this thesis. Checking these ratios with the addition of each explanatory variable will indicate whether the model has a satisfactory goodness-of-fit and if it makes sense to include this variable in the model. Both of the ratios should be close to one before making the final decision on what variables to include in the final model.

Lastly, it is important that the sign of the coefficient agrees with the theoretical expectations of the accident process (i.e., fewer accidents). If any of the above criteria are not met, the explanatory variable should be removed from the model. In this study, SAS software will be used to estimate the regression coefficients and the dispersion parameter using the maximum-likelihood method. The dispersion parameter will indicate how dispersed the data is and whether the use of the negative binomial error structure is justified.

### *4.1.1 Elasticity Analysis*

In addition to estimating the coefficients of the model, elasticity analysis will be carried out. Elasticity analysis estimates the effect of proportional change rather than looking at the sensitivities individually. The advantage of doing elasticity analysis is that the elasticity values can be compared amongst all the explanatory variables. This is not possible with sensitivity analysis as some of the explanatory variables are measured in different units. For example, the seatbelt wearing rate is measured in percentage values, restricting its values between 0 and 1, but the urban speed limit is measured in km/h and has no such restrictions. This means that the sensitivity of E(Y) using changes in the seatbelt wearing rate may not be comparable to the sensitivity of E(Y) using changes in the urban speed limit.

Elasticity is defined as:

$$e_{x_{ij}}^{E(Y)_j} = \frac{\partial E(Y)_j}{\partial x_{ij}} \cdot \frac{x_{ij}}{E(Y)_j} \tag{11}$$

where $E(Y)_j$ is the predicted number of fatalities for country j as defined in equation (7) and $x_{ij}$ is the value of the explanatory variable i for country j. Differentiating equation (7) and applying equation (11) results in the following elasticity function:

$$e_{x_{ij}}^{E(Y)_j} = b_i x_{ij} \tag{12}$$

where $b_i$ is the parameter estimate of explanatory variable i follows (Poch & Mannering, 1996).

This thesis evaluates the elasticity using finite intervals ($\Delta$). The formulation is as follows:

$$e_{x_{ij}}^{E(Y)_j} = \frac{\%\Delta E(Y)}{\%\Delta x} \tag{13}$$

where %ΔE(Y) represents the percentage change in the number of predicted fatalities based on the percentage change (sensitivity) in the x variable (%Δx). For example, if a 2% increase of explanatory variable x causes a 5% increase in the value of E(Y), the elasticity of that variable will equal 2.5. The relative impact of an explanatory variable can be explained by the elasticity (Ulfarsson & Mannering, 2004).

## 4.2 Data

The data for this chapter is the same data that was used in chapter 3. The main difference is the set of variables that were considered to construct the models. This chapter used data for the year 2007 which was readily available from the World Databank (2012) and the World Health Organization (WHO) Global Status Report on Road Safety (2009). Starting off with data for the 178 WHO member countries, the generalized linear models developed in this study use anywhere from 48 to 63 countries. The reason that more than half of the countries were lost during the development is due to the lack of available data and complete datasets for certain countries. If a country does not have a complete dataset, it is automatically excluded from the usable dataset. Table 23 lists the countries that were used in the development of the three models.

**Table 23 – List of countries for each model**

| Model 1 | Model 2 | Model 3 |
|---|---|---|
| 1. Albania | 1. Australia | 1. Australia |
| 2. Australia | 2. Austria | 2. Austria |
| 3. Austria | 3. Belgium | 3. Belgium |
| 4. Belgium | 4. Brazil | 4. Brazil |
| 5. Brazil | 5. Burundi | 5. Burundi |
| 6. Brunei Darussalam | 6. Canada | 6. Canada |
| 7. Burundi | 7. Chad | 7. Chad |
| 8. Canada | 8. Chile | 8. Chile |
| 9. Chad | 9. Congo, Dem. Rep. | 9. Congo, Dem. Rep. |
| 10. Chile | 10. Cyprus | 10. Cyprus |
| 11. Congo, Dem. Rep. | 11. Czech Republic | 11. Czech Republic |
| 12. Cuba | 12. Ecuador | 12. Ecuador |
| 13. Cyprus | 13. Estonia | 13. Estonia |
| 14. Czech Republic | 14. Fiji | 14. Fiji |
| 15. Dominican Republic | 15. Finland | 15. Finland |
| 16. Ecuador | 16. France | 16. France |
| 17. Estonia | 17. Germany | 17. Germany |
| 18. Fiji | 18. Greece | 18. Greece |
| 19. Finland | 19. Honduras | 19. Honduras |
| 20. France | 20. Hungary | 20. Hungary |
| 21. Germany | 21. Iceland | 21. Iceland |
| 22. Greece | 22. Ireland | 22. Ireland |
| 23. Honduras | 23. Israel | 23. Israel |
| 24. Hungary | 24. Italy | 24. Italy |
| 25. Iceland | 25. Japan | 25. Latvia |
| 26. Ireland | 26. Latvia | 26. Malta |
| 27. Israel | 27. Malta | 27. Marshall Islands |
| 28. Italy | 28. Marshall Islands | 28. Mauritius |
| 29. Jamaica | 29. Mauritius | 29. Micronesia, Fed. Sts. |
| 30. Jordan | 30. Micronesia, Fed. Sts. | 30. Morocco |
| 31. Korea, Rep. | 31. Morocco | 31. Namibia |
| 32. Latvia | 32. Namibia | 32. Netherlands |
| 33. Malta | 33. Netherlands | 33. New Zealand |
| 34. Marshall Islands | 34. New Zealand | 34. Norway |
| 35. Mauritius | 35. Norway | 35. Oman |
| 36. Micronesia, Fed. Sts. | 36. Oman | 36. Peru |
| 37. Morocco | 37. Peru | 37. Poland |
| 38. Namibia | 38. Poland | 38. Portugal |
| 39. Netherlands | 39. Portugal | 39. Romania |
| 40. New Zealand | 40. Romania | 40. Serbia |
| 41. Nigeria | 41. Serbia | 41. Spain |
| 42. Norway | 42. Spain | 42. Suriname |
| 43. Oman | 43. Suriname | 43. Sweden |
| 44. Paraguay | 44. Sweden | 44. Switzerland |
| 45. Peru | 45. Switzerland | 45. Tanzania |
| 46. Poland | 46. Tanzania | 46. Thailand |
| 47. Portugal | 47. Thailand | 47. Timor-Leste |
| 48. Qatar | 48. Timor-Leste | 48. United Kingdom |
| 49. Romania | 49. United Kingdom | |

| Model 1 | Model 2 | Model 3 |
|---|---|---|
| 50. Russian Federation<br>51. Serbia<br>52. Solomon Islands<br>53. Spain<br>54. Sri Lanka<br>55. Suriname<br>56. Sweden<br>57. Switzerland<br>58. Syrian Arab Republic<br>59. Tanzania<br>60. Thailand<br>61. Timor-Leste<br>62. United Arab Emirates<br>63. United Kingdom | 50. United States | |

Section 4.1 explained in detail how to develop generalized linear models. Starting off with a simple base model, explanatory variables are added one by one to the model until an acceptable model is developed. Table 24 shows a list of the potential exposure variables and explanatory variables that were taken into consideration during the model development stage. Section 3.1.1 discussed what effect the explanatory variables had on safety. The full model development will be discussed further in the following section.

**Table 24 – List of possible exposure and explanatory variables**

| Exposure Variables | Explanatory Variables |
|---|---|
| Population | Health Expenditure (% of the GDP) |
| Number of Registered Vehicles | Urban Speed Limit (km/h) |
| Total Road Network (km) | Rural Speed Limit (km/h) |
| Vehicles per km of Road | Seatbelt Wearing Rate in Front Seats (%) |
| | Seatbelt Wearing Rate in Rear Seats (%) |
| | Helmet Use by Motorcyclists (%) |
| | Total Percentage of Roads Paved (%) |

## 4.3 Analysis and Results

Following the guidelines discussed in Section 4.1, model development started with simple base models. To start, four base models were developed with the four exposure variables listed in Table 24: population, number of registered vehicles, total road network, and number of vehicles per kilometer of road. All four of these base models showed satisfactory goodness-of-fits so further development was acceptable. From here, explanatory variables were added one by one to each base model to develop the best-fit model. Consequently, two of the base models (total road network and number of vehicles per kilometer of road) were removed from further development due to the low number of observations and the numerous insignificant variables present in these models.

In the end, three full models were developed. The first model uses population as its exposure variable and three explanatory variables. The second and third model both use the number of registered vehicles as its exposure variable along with three explanatory variables. Three explanatory variables was the most that could be used in this study as the addition of more explanatory variables significantly decreased the number of observations and resulted in models with unsatisfactory goodness-of-fit values.

The following subsections provide detailed results of the developed models. Section 4.3.1-4.3.3 defines the developed models; section 4.3.4 discusses the rankings and comparisons of the predicted versus the observed number of fatalities for each country in the model, and section 4.3.5 looks at the elasticity analysis of the variables.

### *4.3.1 Model 1*

Model 1 was selected using the discussed criteria. The model is shown in equation (14).

$$E(Y) = e^{-8.8992} * pop^{1.0246} * e^{(-0.0050*beltfront)+(-0.1012*healthexp)+(0.0076*speedurb)} \tag{14}$$

where E(Y) = number of predicted fatalities. Table 25 shows complete estimation results for this model. The model has 63 observations with a scaled deviance value of 64.9086 (1.1191) and a Pearson $\chi^2$ value of 42.2152 (0.7278). The model uses population (pop) as the exposure variable and contains three explanatory variables: the percentage of people wearing seatbelts in the front seats (beltfront), the health expenditure (healthexp) as a percentage of the GDP, and the urban speed limit (speedurb). It can be seen that these variables are significant at the 90% confidence level. The reason that this model only has three explanatory variables is due to the fact that the addition of additional explanatory variables significantly decreased the number of observations and resulted in the variables becoming insignificant as well as not generating an acceptable goodness-of-fit model. The signs of the estimation values indicate if the parameter contributes to an increase or a decrease in the number of fatalities. It can be seen that both the percentage of people wearing seatbelts in the front seats and the health expenditure as a percentage of the GDP have a negative sign, meaning they contribute to a decrease in the number of fatalities. The urban speed limit, on the other hand, has a positive sign, indicating it contributes to an increase in the number of fatalities. These signs agree with the theoretical expectations of the accident process (e.g. an increase in the percentage of people wearing seatbelts should reduce the number of fatalities). It should be noted that the input values *for beltfront and healthexp are* entered as a percentage number rather than an integer value. For example, if the seatbelt wearing is 85% it should be entered into the model as 85, not as 0.85. The dispersion parameter of 0.2309 confirms that the data was overdispersed and justifies the use of the negative binomial error structure.

**Table 25 – Estimation results for Model 1**

| Parameter | Description | Estimate | Std Error | ρ-value |
|---|---|---|---|---|
| Intercept | - | -8.8992 | 0.7109 | < 0.0001 |
| Pop | population (exposure variable) | 1.0246 | 0.0388 | < 0.0001 |
| Beltfront | seat belt wearing rate in front seat (%) | -0.0050 | 0.0027 | 0.0637 |
| Healthexp | health expenditure (% of GDP) | -0.1012 | 0.0258 | <0.0001 |
| Speedurb | urban speed limit (km/h) | 0.0076 | 0.0045 | 0.0932 |
| **Goodness of Fit** | | | | |
| Number of Observations (n) | | 63 | | |
| Number of Parameters in Model (p) | | 4 | | |
| Degrees of Freedom (n-p-1) | | 58 | | |
| Scaled Deviance (SD/DOF) | | 64.9086 (1.1191) | | |
| Pearson χ2 (Pearson χ2/DOF) | | 42.2152 (0.7278) | | |

Note: dispersion parameter = 0.2309

### *4.3.2 Model 2*

Table 26 shows complete estimation results for the second model. Model 2 has 50 observations with a scaled deviance value of 53.2678 (1.1837) and a Pearson $\chi^2$ value of 56.5754 (1.2572). The model is shown in equation (15).

$$E(Y) = e^{-3.6467} * regveh^{0.9010} * e^{(-0.0156*beltfront)+(-0.0163*beltrear)+(-0.1058*healthexp)} \quad (15)$$

where E(Y) = number of predicted fatalities. The model uses the number of registered vehicles (regveh) as the exposure variable and contains three explanatory variables: the percentage of people wearing seatbelts in the front seats (beltfront), the percentage of people wearing seatbelts in the rear seats (beltrear), and the health expenditure (healthexp) as a percentage of the GDP. It can be seen that all these variables are significant at the 95% confidence level. All the signs of the estimation values agree with the theoretical expectations of the accident process. All three explanatory variables have negative signs, indicating that they contribute to a decrease in the number of fatalities. Again, it should be noted that all the input values are entered as a percentage number rather than an integer value. The dispersion parameter equals 0.4334 and justifies the choice of using the negative binomial error structure.

**Table 26 – Estimation results for Model 2**

| Parameter | Description | Estimate | Std Error | ρ-value |
|---|---|---|---|---|
| Intercept | - | -3.6467 | 0.6793 | < 0.0001 |
| Regveh | registered vehicles (exposure variable) | 0.9010 | 0.0480 | < 0.0001 |
| Beltfront | seat belt wearing rate in front seat (%) | -0.0156 | 0.0045 | 0.0005 |
| Beltrear | seat belt wearing rate in rear seat (%) | -0.0163 | 0.0039 | <0.0001 |
| Healthexp | health expenditure (% of GDP) | -0.1058 | 0.0288 | 0.0002 |
| **Goodness of Fit** | | | | |
| Number of Observations (n) | | 50 | | |
| Number of Parameters in Model (p) | | 4 | | |
| Degrees of Freedom (n-p-1) | | 45 | | |
| Scaled Deviance (SD/DOF) | | 53.2678 (1.1837) | | |
| Pearson χ2 (Pearson χ2/DOF) | | 56.5754 (1.2572) | | |

Note: dispersion parameter = 0.4334

### *4.3.3 Model 3*

Table 27 shows complete estimation results for the third model. Model 3 has 48 observations with a scaled deviance value of 52.2409 (1.2149) and a Pearson $\chi^2$ value of 59.3085 (1.3793). The model is shown in equation (16).

$$E(Y) = e^{-4.5168} * regveh^{0.8448} * e^{(-0.0165*beltfront)+(-0.0162*beltrear)+(0.0169*speedurb)} \quad (16)$$

where E(Y) = number of predicted fatalities. This model also uses the number of registered vehicles (regveh) as the exposure variable with three explanatory variables. Two of the three variables remain the same as in Model 2: the percentage of people wearing seatbelts in the front seats (beltfront) and the percentage of people wearing seatbelts in the rear seats (beltrear). The third variable is: the urban speed limit (speedurb). It can be seen that all these variables, except the urban speed limit, are significant at the 95% confidence level. The urban speed limit is significant at the 90% confidence level. All the signs of the estimation values agree with the theoretical expectations of the accident process. B*eltfront* and *beltrear* have negative signs, indicating that they contribute to a decrease in the number of fatalities. The urban speed limit variable has a positive sign, indicating that a high value contributes to an increase in the number of fatalities. Notice that the input values for *beltfront* and *beltrear* should be entered as a percentage number rather than an integer value. A dispersion parameter of 0.4786 justifies the use the negative binomial error structure as a value greater than zero indicates that the data is overdispersed.

**Table 27 – Estimation results for Model 3**

| **Parameter** | **Description** | **Estimate** | **Std Error** | **ρ-value** |
|---|---|---|---|---|
| Intercept | - | -4.5168 | 0.8497 | < 0.0001 |
| Regveh | registered vehicles (exposure variable) | 0.8448 | 0.0606 | < 0.0001 |
| Beltfront | seat belt wearing rate in front seat (%) | -0.0165 | 0.0053 | 0.0018 |
| Beltrear | seat belt wearing rate in rear seat (%) | -0.0162 | 0.0047 | 0.0005 |
| Speedurb | urban speed limit (km/h) | 0.0169 | 0.0101 | 0.0933 |
| **Goodness of Fit** | | | | |
| Number of Observations (n) | | 48 | | |
| Number of Parameters in Model (p) | | 4 | | |
| Degrees of Freedom (n-p-1) | | 43 | | |
| Scaled Deviance (SD/DOF) | | 52.2409 (1.2149) | | |
| Pearson χ2 (Pearson χ2/DOF) | | 59.3085 (1.3793) | | |

Note: dispersion parameter = 0.4786

### *4.3.4 Rankings*

Once the models were developed, the predicted number of fatalities was calculated for each country. From here, the difference between the observed number of fatalities and the predicted number of fatalities was calculated and sorted in ascending order. This ranking method is also referred to as the potential for safety improvement (PSI) method. The PSI method was first introduced by McGuigan (1981) and later revised by Persaud, Lyon, & Nguyen (1999). The initial PSI measure was actually denoted as the pseudopotential safety improvement (PPSI) measure and calculated as shown in equation (17).

$$PPSI_i = y_i - E(Y)_i \tag{17}$$

where $E(Y)_i$ represents what was normally expected based on traffic volume alone at similar sites and $y_i$ represented the observed number of crashes. The revised PSI measure proposed the use of the Empirical Bayes estimated expected crashes $\lambda_i$ rather than the observed number of crashes $y_i$. This is shown in equation (18).

$$PSI_i = \lambda_i - E(Y)_i \tag{18}$$

This thesis ranked the countries according to equation (17) using the observed number of fatalities in a country. Both equations show that a country with a larger number of expected fatalities than number of observed fatalities will have a smaller PSI value. Lan & Persaud (2011, p. 118) stated that "larger values of $\mu_i$ will decrease the corresponding probability because the PSI is diminished with the increase of $\mu_i$. Thus, sites ranked as unsafe by the PSI method could indeed have no safety issue because of a low $\mu_i$, and vice versa." With this explanation in mind, it should be noted that this ranking does not actually indicate how well a country performs in the safety category but rather that it is more of a representation of how a country actually performed (observed fatalities) compared to what the model predicts its fatalities should be. The predicted values indicate what is normally expected and the difference indicates how far or how close the country is to the normal, expected conditions. The following paragraphs and tables present the results of these rankings. Table 28, Table 29, and Table 30 display the calculated predicted number of fatalities and the ranking results for Model 1, Model 2, and Model 3, respectively.

As seen in Table 28, Nigeria presents the largest difference between the number of observed fatalities and the number of predicted fatalities and therefore ranks number 1. According to the data for Nigeria, the number of fatalities was predicted to be 17,915 but the number of observed (recorded) fatalities was only 4673. For the Democratic Republic of Congo, the predicted number of fatalities was 7256 but the observed number of fatalities was only 281. There are several reasons that could contribute to this. First, it should be remembered that just because a country ranks as unsafe by the PSI method, there might not be any safety issues (Lan & Persaud, 2011). Secondly, in order for a fatality to be observed, it has to be reported to and recorded by the police. In many developing countries, traffic fatalities often go unrecorded and not recording these fatalities would result in a lower number of observed fatalities than is actually the case. If these countries are expected to have a high number of fatalities, like Nigeria and the Democratic Republic of Congo, the difference between the two numbers would be quite large. In addition, as can be seen in Appendix C, there is a wide variety of what is considered a fatality amongst the 178 WHO member countries. Some define a traffic fatality only a fatality if the person dies at the scene, whereas other countries define a fatality as fatality if the person dies within 7 days, 30 days, or even a year after the accident occurs. A country that defines a fatality as dead on the scene will generally record less observed fatalities than a country that defines a fatality as a year after the accident. The model does not take this definition into account but it could explain the position of some of these countries. For example, as seen in Appendix C, Brazil defines a fatality as dead within 1 year and 1 day of the crash where as Congo (Dem. Rep.) defines a fatality as dead at the scene. Naturally, Brazil will record more observed fatalities than Congo (Dem. Rep.) since their observation period is much longer. If Congo (Dem. Rep.) used the same definition as Brazil, their number of observed fatalities would have been much higher and subsequently their PSI ranking would be better as the difference between the observed and predicted number of fatalities would have decreased. This shows how important it is to try and standardize the definition of a fatality.

If the number of predicted fatalities is lower than the number of observed fatalities, as is the case for any of the countries whose difference value yields a positive value, it means that the country actually recorded more observed fatalities than what was predicted.

Table 28 – Rankings for Model 1

| Country | Observed Fatalities | Predicted Fatalities | Difference | Rank |
|---|---|---|---|---|
| Nigeria | 4673 | 17915 | -13242 | 1 |
| Congo, Dem. Rep. | 281 | 7256 | -6975 | 2 |
| Tanzania | 2595 | 6103 | -3508 | 3 |
| United Kingdom | 3298 | 5123 | -1825 | 4 |
| Thailand | 12492 | 13959 | -1467 | 5 |
| Chad | 840 | 2004 | -1164 | 6 |
| Germany | 4949 | 5527 | -578 | 7 |
| Spain | 4104 | 4561 | -457 | 8 |
| Netherlands | 791 | 1154 | -363 | 9 |
| Sri Lanka | 2334 | 2690 | -356 | 10 |
| Morocco | 3838 | 4157 | -319 | 11 |
| Burundi | 65 | 374 | -309 | 12 |
| Israel | 398 | 632 | -234 | 13 |
| Sweden | 471 | 680 | -209 | 14 |
| Switzerland | 370 | 494 | -124 | 15 |
| Norway | 233 | 356 | -123 | 16 |
| Peru | 3510 | 3615 | -105 | 17 |
| Qatar | 199 | 296 | -97 | 18 |
| Finland | 380 | 439 | -59 | 19 |
| Australia | 1616 | 1663 | -47 | 20 |
| Fiji | 59 | 93 | -34 | 21 |
| Solomon Islands | 19 | 51 | -32 | 22 |
| Syrian Arab Republic | 2818 | 2843 | -25 | 23 |
| Mauritius | 140 | 165 | -25 | 24 |
| Cyprus | 89 | 108 | -19 | 25 |
| Brunei Darussalam | 54 | 72 | -18 | 26 |
| Ireland | 365 | 380 | -15 | 27 |
| Malta | 14 | 29 | -15 | 28 |
| Timor-Leste | 46 | 60 | -14 | 29 |
| Micronesia, Fed. Sts. | 2 | 5 | -3 | 30 |
| Marshall Islands | 1 | 2 | -1 | 31 |
| Jamaica | 350 | 345 | 5 | 32 |
| Iceland | 30 | 21 | 9 | 33 |
| Paraguay | 845 | 830 | 15 | 34 |
| Albania | 384 | 364 | 20 | 35 |
| Ecuador | 1801 | 1764 | 37 | 36 |
| Suriname | 90 | 44 | 46 | 37 |
| Estonia | 196 | 144 | 52 | 38 |
| United Arab Emirates | 1056 | 973 | 83 | 39 |
| New Zealand | 423 | 322 | 101 | 40 |
| Portugal | 854 | 746 | 108 | 41 |
| Namibia | 368 | 250 | 118 | 42 |

| Country | Observed Fatalities | Predicted Fatalities | Difference | Rank |
|---|---|---|---|---|
| Italy | 5669 | 5549 | 120 | 43 |
| Austria | 691 | 560 | 131 | 44 |
| Romania | 2712 | 2569 | 143 | 45 |
| Jordan | 992 | 846 | 146 | 46 |
| Cuba | 994 | 825 | 169 | 47 |
| Latvia | 407 | 219 | 188 | 48 |
| Chile | 2280 | 2089 | 191 | 49 |
| Oman | 798 | 606 | 192 | 50 |
| Czech Republic | 1222 | 1011 | 211 | 51 |
| Canada | 2889 | 2664 | 225 | 52 |
| Honduras | 974 | 720 | 254 | 53 |
| Hungary | 1232 | 974 | 258 | 54 |
| Belgium | 1067 | 802 | 265 | 55 |
| Dominican Republic | 1414 | 1098 | 316 | 56 |
| Serbia | 962 | 625 | 337 | 57 |
| Korea, Rep. | 6166 | 5800 | 366 | 58 |
| France | 4620 | 3960 | 660 | 59 |
| Greece | 1657 | 847 | 810 | 60 |
| Poland | 5583 | 4212 | 1371 | 61 |
| Russian Federation | 33308 | 23889 | 9419 | 62 |
| Brazil | 35155 | 20785 | 14370 | 63 |

Table 29 – Rankings for Model 2

| Country | Observed Fatalities | Predicted Fatalities | Difference | Rank |
|---|---|---|---|---|
| Japan | 6639 | 30957 | -24318 | 1 |
| Thailand | 12492 | 33655 | -21163 | 2 |
| Italy | 5669 | 24454 | -18785 | 3 |
| Spain | 4104 | 9006 | -4902 | 4 |
| Poland | 5583 | 6897 | -1314 | 5 |
| Portugal | 854 | 1905 | -1051 | 6 |
| Serbia | 962 | 1805 | -843 | 7 |
| Belgium | 1067 | 1747 | -680 | 8 |
| Switzerland | 370 | 947 | -577 | 9 |
| United Kingdom | 3298 | 3862 | -564 | 10 |
| Austria | 691 | 1235 | -544 | 11 |
| Greece | 1657 | 2180 | -523 | 12 |
| Cyprus | 89 | 533 | -444 | 13 |
| Romania | 2712 | 3132 | -420 | 14 |
| Hungary | 1232 | 1639 | -407 | 15 |
| Netherlands | 791 | 1196 | -405 | 16 |
| Finland | 380 | 768 | -388 | 17 |
| Israel | 398 | 740 | -342 | 18 |
| Ireland | 365 | 620 | -255 | 19 |
| Latvia | 407 | 599 | -192 | 20 |
| Sweden | 471 | 620 | -149 | 21 |
| Malta | 14 | 162 | -148 | 22 |
| Mauritius | 140 | 280 | -140 | 23 |
| Norway | 233 | 365 | -132 | 24 |
| Iceland | 30 | 69 | -39 | 25 |
| Estonia | 196 | 230 | -34 | 26 |
| Suriname | 90 | 116 | -26 | 27 |
| Marshall Islands | 1 | 5 | -4 | 28 |
| Micronesia, Fed. Sts. | 2 | 3 | -1 | 29 |
| Namibia | 368 | 367 | 1 | 30 |
| New Zealand | 423 | 421 | 2 | 31 |
| Timor-Leste | 46 | 44 | 2 | 32 |
| Fiji | 59 | 31 | 28 | 33 |
| Burundi | 65 | 27 | 38 | 34 |
| Oman | 798 | 754 | 44 | 35 |
| Congo, Dem. Rep. | 281 | 180 | 101 | 36 |
| Australia | 1616 | 1507 | 109 | 37 |
| Ecuador | 1801 | 1634 | 167 | 38 |
| Czech Republic | 1222 | 1024 | 198 | 39 |
| Chad | 840 | 635 | 205 | 40 |
| Honduras | 974 | 699 | 275 | 41 |
| Chile | 2280 | 1886 | 394 | 42 |

| Country | Observed Fatalities | Predicted Fatalities | Difference | Rank |
|---|---|---|---|---|
| Germany | 4949 | 4394 | 555 | 43 |
| Canada | 2889 | 1944 | 945 | 44 |
| Tanzania | 2595 | 1281 | 1314 | 45 |
| France | 4620 | 3197 | 1423 | 46 |
| Morocco | 3838 | 1841 | 1997 | 47 |
| Peru | 3510 | 953 | 2557 | 48 |
| Brazil | 35155 | 19363 | 15792 | 49 |
| United States | 42642 | 14249 | 28393 | 50 |

Table 30 – Rankings for Model 3

| Country | Observed Fatalities | Predicted Fatalities | Difference | Rank |
|---|---|---|---|---|
| Thailand | 12492 | 28966 | -16474 | 1 |
| Italy | 5669 | 20903 | -15234 | 2 |
| Spain | 4104 | 7861 | -3757 | 3 |
| Serbia | 962 | 2612 | -1650 | 4 |
| Portugal | 854 | 2066 | -1212 | 5 |
| Belgium | 1067 | 1834 | -767 | 6 |
| Switzerland | 370 | 1108 | -738 | 7 |
| Austria | 691 | 1369 | -678 | 8 |
| Greece | 1657 | 2323 | -666 | 9 |
| Oman | 798 | 1350 | -552 | 10 |
| Netherlands | 791 | 1223 | -432 | 11 |
| Cyprus | 89 | 435 | -346 | 12 |
| Finland | 380 | 689 | -309 | 13 |
| Israel | 398 | 643 | -245 | 14 |
| Mauritius | 140 | 353 | -213 | 15 |
| Hungary | 1232 | 1434 | -202 | 16 |
| Ireland | 365 | 553 | -188 | 17 |
| Malta | 14 | 178 | -164 | 18 |
| Norway | 233 | 363 | -130 | 19 |
| Sweden | 471 | 600 | -129 | 20 |
| Latvia | 407 | 524 | -117 | 21 |
| Timor-Leste | 46 | 122 | -76 | 22 |
| Iceland | 30 | 82 | -52 | 23 |
| Namibia | 368 | 419 | -51 | 24 |
| Marshall Islands | 1 | 15 | -14 | 25 |
| Suriname | 90 | 99 | -9 | 26 |
| Burundi | 65 | 68 | -3 | 27 |
| Micronesia, Fed. Sts. | 2 | 4 | -2 | 28 |
| New Zealand | 423 | 404 | 19 | 29 |
| Estonia | 196 | 168 | 28 | 30 |
| Fiji | 59 | 23 | 36 | 31 |
| United Kingdom | 3298 | 3216 | 82 | 32 |
| Congo, Dem. Rep. | 281 | 184 | 97 | 33 |
| Canada | 2889 | 2772 | 117 | 34 |
| Australia | 1616 | 1318 | 298 | 35 |
| Ecuador | 1801 | 1494 | 307 | 36 |
| Chad | 840 | 499 | 341 | 37 |
| Chile | 2280 | 1882 | 398 | 38 |
| Czech Republic | 1222 | 774 | 448 | 39 |
| Honduras | 974 | 467 | 507 | 40 |
| Germany | 4949 | 4409 | 540 | 41 |
| Romania | 2712 | 2094 | 618 | 42 |

| Country | Observed Fatalities | Predicted Fatalities | Difference | Rank |
|---|---|---|---|---|
| Poland | 5583 | 4880 | 703 | 43 |
| France | 4620 | 3473 | 1147 | 44 |
| Tanzania | 2595 | 1054 | 1541 | 45 |
| Morocco | 3838 | 1512 | 2326 | 46 |
| Peru | 3510 | 789 | 2721 | 47 |
| Brazil | 35155 | 26244 | 8911 | 48 |

### *4.3.5 Elasticity Analysis*

The values presented in Table 31, Table 32, and Table 33 are the elasticity values of the explanatory variables for Models 1, 2 and 3, respectively. The interpretation of the elasticity values is fairly straightforward. When interpreting the elasticity values, the sign of the values should be ignored and should instead be interpreted using the absolute value. The following rules explain how to interpret the elasticity values presented in the tables below (Moffatt, n.d.):

- $e_{x_{ij}}^{E(Y)_j} < 1$ → inelastic
- $e_{x_{ij}}^{E(Y)_j} = 1$ → unit elastic
- $e_{x_{ij}}^{E(Y)_j} > 1$ → elastic

This means that when the elasticity value is less than one, the outcome is not very sensitive to change. When the elasticity value is greater than one, on the other hand, the outcome is very sensitive to change. For example, an elasticity value of 3.5 indicates that the variable is elastic and that the outcome is very sensitive to a change in this variable. The elasticity value represents the proportional change of the outcome (number of predicted fatalities) when an explanatory variable changes from one value to another (sensitivity). In order to conduct this analysis correctly, only one explanatory variable can change at a time and the other variables must remain constant.

The sensitivity values for each of the explanatory variables presented in Model 1, 2, and 3 were as follows:

- Seatbelt wearing rate in front seats = ±5% and ±10%
- Seatbelt wearing rate in rear seats = ±5% and ±10%
- Health expenditure as a percentage of GDP = ±1%, ±2.5%, and ±5%
- Urban speed limit = ±5%, ±10%, and ±15%

The motive behind using smaller percentage values for the health expenditure variable has to do with the fact that this value is a percentage of the total GDP. It is highly unlikely that a country will increase or decrease its health expenditure by more than 5%. Therefore, the sensitivity values for that variable were reduced to more reasonable values.

Table 31 presents the elasticity analysis results for Model 1. It can be noted that the first and third variable (seatbelt wearing rate in front seats and urban speed limit, respectively) are considered inelastic. This indicates that the outcome of the model is not sensitive to the changes in these variables as the elasticity values are less than one. On the contrary, the second variable (health expenditure) is extremely elastic as the elasticity values are much greater than one. With regards to the first variable, increasing the seatbelt wearing rate in front seats by 5% resulted in an elasticity value of 0.4938. This means that a 5% increase in this variable would roughly correspond to a 2.5% decrease in the number of predicted fatalities. For a decrease of 5% of the urban speed limit, the elasticity value is 0.5989. This means that the number of predicted fatalities would decrease by roughly 3%. Now, as stated earlier, the biggest proportional change can be seen when changing the health expenditure values. Although it is highly unlikely that a country will increase its current health expenditure by 5%, doing so would roughly result in a 40% decrease in the number of predicted fatalities (elasticity = 7.9420). The highly elastic values of the health expenditure variable underscore the importance of health expenditure on the number of fatalities. These results are the same for all the countries in Model 1, under the condition that all other variables (population, health expenditure, and urban speed limit) remain constant. It should be noted that even though the elasticity values are interpreted using the absolute value, the sign indicates whether the outcome (number of fatalities) is affected negatively or positively. The first and second variable affect the outcome positively as an increase in this variable (positive sensitivity) results in a decreased number of fatalities. A decrease in this variable (negative sensitivity) has a negative effect on the outcome as it would result in an increased number of fatalities. The third variable has the opposite effect on the outcome. An increase in this variable results in an increased number of fatalities, and a decrease in the variable results in a decreased number of fatalities.

**Table 31 – Elasticity analysis results for Model 1**

| Variable | Sensitivity % | ΔE(A) | Elasticity |
|---|---|---|---|
| **Seat Belt Wearing Rate in Front Seats** | -10% | 5.13% | -0.5127 |
| | -5% | 2.53% | -0.5063 |
| | 0% | - | - |
| | +5% | -2.47% | -0.4938 |
| | +10% | -4.88% | -0.4877 |
| **Health Expenditure (% of GDP)** | -5% | 65.86% | -13.1729 |
| | -2.5% | 28.79% | -11.5153 |
| | -1% | 10.65% | -10.6498 |
| | 0% | - | - |
| | +1% | -9.62% | -9.6248 |
| | +2.5% | -22.35% | -8.9413 |
| | +5% | -39.71% | -7.9420 |
| **Urban Speed Limit** | -15% | -8.72% | 0.5811 |
| | -10% | -5.90% | 0.5899 |
| | -5% | -2.99% | 0.5989 |
| | 0% | - | - |
| | +5% | 3.09% | 0.6173 |
| | +10% | 6.27% | 0.6269 |
| | +15% | 9.55% | 0.6366 |

Note: Elasticity values are interpreted using the absolute value

Table 32 shows the elasticity results for Model 2. In the case of this model, all three variables are elastic since the elasticity values are all greater than one. The seatbelt wearing rate variables yield similar results but it can be noted that the health expenditure variable has a much greater elasticity than the other two variables. This means that a change in the health expenditure variable has a greater effect on the number of fatalities for the countries in Model 2 than a change in the seatbelt wearing rates in front or rear seats. A 5% increase in the first variable has an elasticity value of 1.5007 which would result in a 7.5% decrease in the number of fatalities. A 5% increase in the second variable has an elasticity value of 1.5653, and would result in a 7.8% decrease in the number of fatalities. Lastly, a 5% increase in the third variable has an elasticity value of 8.2126 which would roughly result in a 41% decrease in the number of fatalities. These three examples show that the health expenditure variable has indeed the greatest and most important effect on this model. Also, when comparing the seatbelt wearing rate in front seats variable of Model 1 and Model 2, it can be seen that the number of fatalities is more sensitive to a change in this variable in Model 2 than in Model 1. A 5% increase of this variable would result in a 2.5% decrease in the number of fatalities for Model 1 and a 7.5% decrease in the number of fatalities for Model 2. All three of the variables have a positive effect on the outcome when increased (positive sensitivity) and a negative effect when decreased (negative sensitivity).

**Table 32 – Elasticity analysis results for Model 2**

| Variable | Sensitivity % | ΔE(A) | Elasticity |
|---|---|---|---|
| **Seat Belt Wearing Rate in Front Seats** | -10% | 16.88% | -1.6883 |
| | -5% | 8.11% | -1.6225 |
| | 0% | - | - |
| | +5% | -7.50% | -1.5007 |
| | +10% | -14.44% | -1.4444 |
| **Seat Belt Wearing Rate in Rear Seats** | -10% | 17.70% | -1.7704 |
| | -5% | 8.49% | -1.6983 |
| | 0% | - | - |
| | +5% | -7.83% | -1.5653 |
| | +10% | -15.04% | -1.5041 |
| **Health Expenditure (% of GDP)** | -5% | 69.72% | -13.9447 |
| | -2.5% | 30.28% | -12.1112 |
| | -1% | 11.16% | -11.1600 |
| | 0% | - | - |
| | +1% | -10.04% | -10.0395 |
| | +2.5% | -23.24% | -9.2964 |
| | +5% | -41.08% | -8.2161 |

Note: Elasticity values are interpreted using the absolute value

Table 33 presents the elasticity results for Model 3. As was also the case for Model 2, the seatbelt wearing rate in the front seats and the rear seats yield similar elasticity values. This indicates that they have similar effects on the final outcome. These two variables can also be considered elastic variables since their elasticity values are greater than one. The third variable is considered inelastic. This means that the outcome is more sensitive to a change in the first two variables than a change in the third variable. An increase of 5% in the first variable produces an elasticity value of 1.5838 which roughly indicates a 7.92% decrease in the outcome. A 5% increase in the second variable produces an elasticity value of 1.5561 and roughly indicates a 7.78% decrease in the outcome. These two values are very similar. A 5% decrease in the third variable, however, only has an elasticity value of 0.8274 which indicates a 4.14% decrease in the outcome. Similar to Model 1, the first two variables in Model 3 affect the outcome positively when increased (positive sensitivity) and negatively when decreased (negative sensitivity). The third variable has the opposite effect on the outcome and affects the outcome positively when decreased and negatively when increased.

**Table 33 – Elasticity analysis results for Model 3**

| Variable | Sensitivity % | ΔE(A) | Elasticity |
|---|---|---|---|
| **Seat Belt Wearing Rate in Front Seats** | -10% | 17.94% | -1.7939 |
| | -5% | 8.60% | -1.7200 |
| | 0% | - | - |
| | +5% | -7.92% | -1.5838 |
| | +10% | -15.21% | -1.5211 |
| **Seat Belt Wearing Rate in Rear Seats** | -10% | 17.59% | -1.7586 |
| | -5% | 8.44% | -1.6874 |
| | 0% | - | - |
| | +5% | -7.78% | -1.5561 |
| | +10% | -14.96% | -1.4956 |
| **Urban Speed Limit** | -15% | -11.90% | 0.7936 |
| | -10% | -8.10% | 0.8103 |
| | -5% | -4.14% | 0.8274 |
| | 0% | - | - |
| | +5% | 4.32% | 0.8631 |
| | +10% | 8.82% | 0.8817 |
| | +15% | 13.51% | 0.9009 |

Note: Elasticity values are interpreted using the absolute value

The general trend in all of the models is that increasing the seatbelt wearing rate in front seats, increasing the seatbelt wearing rate in rear seats, or increasing the health expenditure would result in a decreased number of fatalities and a decrease in these variables would result in an increased number of fatalities. With regards to the urban speed limit variable, however, the number of fatalities will be decreased only if the speed limit is decreased. In both Model 1 and Model 2, the health expenditure variable was by far the most elastic variable. In terms of fatality reduction, it would be most beneficial for the countries in those models to increase their health expenditure. On the other hand, for Model 3, the seatbelt wearing rate in the front and rear seats were the most elastic variables. For this reason, it would be more beneficial for countries in this model (Model 3) to increase the seatbelt wearing rate in the front and rear seats rather than decreasing the urban speed limit.

# 5. Comparison of the Two Techniques

This chapter will look at a brief comparison between the two techniques presented in Chapter 3 and Chapter 4. Although the two techniques are independent of one another and the ranking methods are quite different, both techniques look at finding alternative ways of evaluating the road safety performance of different countries around the world rather than just analyzing their performance based on one indicator – the number of road traffic fatalities per million inhabitants.

Chapter 3 developed a composite road safety performance index using the data envelopment analysis (DEA) weighting method. This method combined, integrated, and converted multiple road safety performance indicator values for each country into a single value called an efficiency score. This efficiency score was then used to rank the countries. A score of 1.000 indicated that the country was efficient with regards to road safety performance and any country that scored higher than one was said to be underperforming. This means that the countries were ranked in ascending order with a country ranked number 1 having a better road safety performance than a country that ranked number 10. The ranking method used in Chapter 3 gives countries a more insightful way of comparing their road safety performance with other countries around the world as it considers numerous contributing factors. It lets them see how they perform compared to the other countries and allows them to set targets and benchmarks so they can improve their overall road safety performance.

Chapter 4 used the generalized linear modeling method to develop three accident prediction models on a global scale using various road safety performance indicators as the explanatory variables. Once the models were developed, the number of predicted fatalities was calculated for each of the countries. Instead of using the more traditional method of ranking the countries based on the number of fatalities, the countries were ranked according to the potential for safety improvement (PSI) method. The PSI method calculates the difference between the observed number of fatalities and the predicted number of fatalities and ranks accordingly. The countries were ranked in ascending order with the largest negative PSI value receiving rank number 1. If a country had a negative PSI value it meant that their number of predicted fatalities was greater than the number of observed fatalities indicating that the country actually performed better than what was expected whereas a positive value indicated that the country performed worse than what was expected. If a country received a PSI value close to zero, it meant that the country performed as expected and the number of observed fatalities roughly equaled the number of predicted fatalities. The PSI ranking method shows which countries have the highest potential for improvement. A country ranked near the bottom has the greatest potential for improvement as it would indicate that it is observing more fatalities than what would normally be expected for that country. It illustrates that the country has the opportunity to reduce its number of fatalities. The elasticity analysis done in this chapter would help the country identify what change would have the greater effect on the outcome.

Since the two methods used in this thesis are so different, it is difficult to compare the results. The main difference between the two ranking methods is that the ranking in Chapter 3 is really the only ranking method that can be used to assess the road safety performance level as countries ranked unsafe by the PSI method in Chapter 4 could potentially have no safety issues. This was explained by Lan & Persaud (2011). However, one comparison that can be made is that in Chapter 3 countries like Japan, Sweden, Switzerland, Norway, United Kingdom, and Germany generally ranked amongst the best performing countries. In the ranking in Chapter 4, these same countries generally have negative PSI values indicating that they are performing better than what is being predicted by the models.

Another comparison that can be made is between the DEA weights in Chapter 3 and the elasticity analysis in Chapter 4. Both the weights and the elasticity analysis indicate what variables have the greatest impact on the outcome. The main findings in Chapter 3 showed that in Analysis 1, for 3 input variables, the highest country specific weight was either in the percentage of seat belt use in front seats category or the total health expenditure category with most of them being in the total health expenditure category. The results, with regards to the weights for 4 input variables, showed that the highest country specific weight varied more between some of the variables. In particular, the highest weight varied between the percentage of seat belt use in front seats category, the percentage of seat belt use in rear seats category, and the total health expenditure category with about an even split between the percentage of seat belt use in rear seats category and the total health expenditure category. For Analysis 2, the results for all three sub-analyses indicated that most countries received the highest weighting in the first category, percentage of seat belt use in front seats. The elasticity analysis in Chapter 4 clearly indicated that when the total health expenditure indicator was one of the explanatory variables of the model (Model 1 and Model 2) that it had the greatest effect on the outcome, by far. For Model 3, however, which didn't consider the health expenditure variable, the seatbelt wearing rate in the front and rear seats were the most elastic variables and both with roughly the same elasticity. Although the findings about which variable is the most important with regards to the outcome differs somewhat between the methods, both methods seem to agree that the seatbelt wearing rate in front seats, the seatbelt wearing rate in rear seats, and the total health expenditure variables all have a significant effect on the outcome.

In the end, the methods in Chapter 3 and Chapter 4 both use more comprehensive data to provide better insight and deeper understanding of the processes that lead to accidents by using alternative methods to measure and evaluate the road safety performance of different countries around the world.

# 6. Conclusions and Future Work

With the UN General Assembly declaring 2011-2020 as the Decade of Action for Road Safety (World Health Organization, 2012b), road safety has become an increasingly important global issue, as it is their goal to stabilize and reduce the forecasted level of road traffic deaths around the world. In order to contribute to this reduction, more and more research is being conducted to see how this can be done and on which areas one should focus more. It is advantageous for countries to evaluate their road safety performance level and compare it with that of other countries as this may allow them to understand what areas need improvement and assists them in setting targets and benchmarks. This thesis presented two methods of evaluating road safety performance levels. The first method was the data envelopment analysis (DEA) and the second method was the development of accident prediction models.

The first method discussed in this thesis is the data envelopment analysis (DEA) method. This method helped contribute to further research in two ways. Firstly, as was shown in the literature review, most current research focused on European countries. This thesis expanded the list of countries in the dataset by considering a variety of other countries, including both developing and developed countries. The countries taken into consideration are all members of the World Health Organization. Analysis 1 contained 36 countries and Analysis 2 contained 24 countries with data coming from the World Health Organization and the World Data Bank. Secondly, this thesis examined whether adding additional road safety performance variables (inputs) had any effect on a country's efficiency score and ranking.

The DEA method was first used to calculate efficiency scores for each country in the dataset. Then, it was used to investigate the effect on the scores with the addition of extra input variables. The efficiency scores allow the countries to compare their road safety performance level with the other countries in the dataset. Underperforming countries can identify the sources and the amount of inefficiency in each indicator using their country specific weights and set targets and benchmarks to improve their overall score. A country that received a score of one is considered to be efficient and a country with a score higher than one is considered to be inefficient. The efficiency scores in Analysis 1 and Analysis 2 both showed efficiency score improvements with the addition of extra input variables. However, compared to the improvements in Analysis 1, Analysis 2 showed smaller positive jumps in the scores. In Analysis 1, for 3 input variables, Malta was the only country to receive a score of one. The addition of a fourth input variable resulted in the following countries also obtaining an efficiency score of one: the Netherlands, Sweden, and Switzerland. In Analysis 2, for 3 input variables, Japan, Sweden, Switzerland, and Norway obtained a score of one, making them the most efficient countries in the dataset. The addition of the fourth and fifth input variable resulted in the United Kingdom also obtaining a score of one. For both analyses, countries like Poland, Ecuador, Chile, and Oman were amongst the worst performing countries. The country specific weights of each sub-analysis indicated what road safety performance indicator had the greatest effect on the outcome. As shown in Chapter 3 and reiterated in Chapter 5, the highest country specific weight, for Analysis 1, varied between the percentage of seat belt use in front seats category and the total health expenditure category whereas for Analysis 2, most countries had a highest weighting in the percentage of seat belt use in front seats category.

Next, the countries were ranked by sorting the efficiency scores in ascending order and again the change in ranking was investigated with the addition of extra input variables. The change in ranking for Analysis 1 was quite significant as approximately half of the countries improved their standing and the other half declined in their standing. In Analysis 2, there was hardly any difference in the rankings – even though more than half of the countries improved their score. The ranking of each country is relative to the efficiency scores of the other countries, so although an individual country might see an improvement in its score, it may not result in an improvement in the standings. This is due to the fact that the other countries may have also improved their score by the same percentage therefore resulting in no change in the rankings. For example, if country A and country B both improve their score by 1%, they will not change their position in the rankings relative to one another.

Ultimately, it can be stated that, for both analyses, the addition of extra input variables had a positive effect on the efficiency scores. Yet, the additional input variables only had a noteworthy impact on the countries in Analysis 1 and not on the countries in Analysis 2. The DEA analysis is highly sensitive to the amount of data available and is greatly affected by the number of inputs and outputs. Naturally, the more data is available, the more accurate results will be. All the variables used in Chapter 3 had a significant effect on road safety, as was described in Chapter 2. It is not valid to compare the results from

Analysis 1 with the results from Analysis 2 since the datasets are different. It should be noted that highly developed countries were generally more efficient when it comes to road traffic safety. This can be linked to the potential lack of resources available for conducting research and collecting data in developing countries.

The second method discussed in this thesis is the development of accident prediction models on a global level. This thesis developed three models using the generalized linear modeling approach and the negative binomial regression method was used to accommodate the overdispersion of the data. The use of this regression method was justified by the dispersion parameters of each model as they were all greater than zero which indicated that the data was indeed overdispersed. The three models used 63, 50, and 48 countries, respectively, in their development also using data from the World Health Organization and the World Data Bank. Each model consisted of one exposure variable and three explanatory variables. Just like the variables in Chapter 3, the variables in Chapter 4 all had a significant effect on road safety. The number of explanatory variables, in this analysis, was limited to three due to the fact that adding more variables lead to insignificant variables and models with an unsatisfactory goodness-of-fit. The goodness-of-fit of the models was tested using two criteria, the ratio of the Pearson $\chi^2$ to the degree of freedom and the ratio of the scaled deviance to the degree of freedom. If the ratios were close to 1.000, the models were considered satisfactory. All three models did indeed have satisfactory goodness-of-fit measures.

The explanatory variables used amongst the three models varied between the following four: seatbelt wearing rate in front seats, seatbelt wearing rate in rear seats, health expenditure as a percentage of GDP, and the urban speed limit. Each parameter was significant at the 90% or 95% confidence level. Once the models were developed, the number of predicted fatalities was calculated for each of the countries in the datasets. From here, the countries were ranked according to the potential for safety improvement (PSI) method. A PSI value was calculated for each country by finding the difference between the observed number of fatalities and the predicted number of fatalities of that country. The value shows how a country's actual (observed) performance compares to what the model predicts. The predicting values indicate what is "normal" according to the explanatory variables and the difference shows how far or how close a country is to its normal performing conditions. The values were used to rank the countries, in descending order, with the largest negative difference ranking number 1. A large negative PSI value indicated that the country performed better than what was predicted by the model and that they had a high number of predicted fatalities relative to the number of observed fatalities. This included countries such as Thailand, Spain, and the Netherlands. The countries that ranked near the bottom have the highest potential for improvement as the model indicated that they should be able to reduce their number of fatalities based on the indicators considered. This included countries such as Brazil, France, Honduras, and Chile in all three models. One way of explaining the reason behind some developing countries appearing near the top is that they might not be recording all of their fatalities due to lack of resources or lack of reporting. This is why the rankings presented in Chapter 4 should not be used to assess the road safety performance of the countries as a country labelled unsafe according to the PSI method may not actually safety issues, and vice versa (Lan & Persaud, 2011).

Next, elasticity analysis was carried out. The elasticity values represented the proportional change of the outcome (number of predicted fatalities) when an explanatory variable changed from one value to another (sensitivity). The analysis was carried out by changing one explanatory variable at a time while keeping the other variables constant. Countries can determine what variables have a greater importance on the outcome by analyzing the elasticity values. The results, for Model 1 and Model 2, indicated that the health expenditure variable was highly elastic (values much greater than one) and therefore had the greatest impact on the final outcome whereas Model 3 showed that the seatbelt wearing rate in front seats and the seatbelt wearing rate in rear seats had the greatest effect on the final outcome. National transportation agencies can use these values for making strategies or running campaigns to help reduce the number of fatalities in their country.

Chapter 5 looked at a comparison between the two methods. The main difference being that the ranking in Chapter 4 could not be used to assess the road safety performance of the countries. One comparison determined that countries such as Japan, Sweden, Switzerland, Norway, United Kingdom, and Germany generally ranked amongst the best performing countries in Chapter 3 and generally had negative PSI values indicating that they performed better than what was being predicted by the models in Chapter 4. Another comparison investigated if there was any similarity between the results obtained from the DEA weights in Chapter 3 and the elasticity analysis in Chapter 4. As discussed in the paragraphs above, the methods do not completely agree on which variable has the greatest effect on the outcome, but both methods do seem to agree that the seatbelt wearing rate in front seats, the seatbelt wearing rate in rear seats, and the total health expenditure variables are all important.

In summary, the major findings are:

- The efficiency scores in Analysis 1 and Analysis 2 both showed efficiency score improvements with the addition of extra input variables.
- In Analysis 1, for 3 input variables, Malta was the only country to receive a score of one. The addition of a fourth input variable resulted in the following countries also obtaining an efficiency score of one: the Netherlands, Sweden, and Switzerland.
- In Analysis 2, for 3 input variables, Japan, Sweden, Switzerland, and Norway obtained a score of one. The addition of the fourth and fifth input variable resulted in the United Kingdom also obtaining a score of one.
- For Analysis 1, the highest country specific weight varied between the percentage of seat belt use in front seats category and the total health expenditure category.
- For Analysis 2, most countries had a highest weighting in the percentage of seat belt use in front seats category.
- Highly developed countries were generally more efficient.

- The change in ranking for Analysis 1 was quite significant as approximately half of the countries improved their standing and the other half declined in their standing.
- In Analysis 2, there was hardly any difference in the rankings.
- Three models using the generalized linear modeling approach and the negative binomial regression method were developed.
- Countries were ranked according to the potential for safety improvement (PSI) method.
- The elasticity analysis results, for Model 1 and Model 2, indicated that the health expenditure variable was highly elastic and therefore had the greatest impact on the final outcome whereas Model 3 showed that the seatbelt wearing rate in front seats and the seatbelt wearing rate in rear seats had the greatest effect on the final outcome.
- When comparing the methods, countries such as Japan, Sweden, Switzerland, Norway, United Kingdom, and Germany generally ranked amongst the best performing countries in Chapter 3 and generally had negative PSI values indicating that they performed better than what was being predicted by the models in Chapter 4.
- Both methods agree that the seatbelt wearing rate in front seats, the seatbelt wearing rate in rear seats, and the total health expenditure variables are all important in terms of the effect on the final outcome.

In the end, this thesis presented advancement in the evaluation of road safety performance levels of different countries around the world using both the DEA method and accident prediction modeling. Both methods use more comprehensive data to provide better insight and deeper understanding of the processes that lead to accidents by using alternative methods to measure and evaluate the road safety performance of different countries around the world. The inclusion of additional countries in the dataset for the DEA method contributed to the road safety performance evaluation of a wider range of countries, not just European countries. Since there is little prior research, the development of accident prediction models using road safety performance indicators on a global scale is great progression towards alternative ways of evaluating the road safety of different countries as these models should allow countries to predict fatalities on a long-term basis.

It is vital that this research continues. One of the main concentrations should be to continue increasing the datasets by adding more countries and more variables to the analysis. In order to be able to add more countries to the analysis, it is imperative that countries around the world continue with their efforts to collect road safety data and that they increase the number of performance indicators that are evaluated during collection. It is also beneficial to attempt to standardize the systematic approach and methodology for conducting research and collecting data for all countries, as this will make comparisons between countries much easier and more accurate. It was pointed out in both Chapter 3 and Chapter 4 that the addition of extra input variables decreased the size of the dataset. The number of road safety performance indicators for which data is available is quite variable amongst countries around the world particularly due to this lack of standardization. The fact that many countries may not have the resources available to conduct extensive research is also a contributor to this issue. Some developing countries may not have the resources available for conducting such extensive data collecting.

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# Appendices

## Appendix A: Sample DEA Code

**Figure 2 – Sample DEA Code**

```
MODEL:
! Data Envelope Analysis of Road Safety Performance;
 SETS:
  DMU:
     SCORE; ! Each decision making unit has a;
            ! score to be computed;

FACTOR;
! There is a set of factors, input & output;
  DXF(DMU, FACTOR):  F, ! F(I, J) = Jth factor of DMU I;
                     W; ! Weights used to compute DMU I's score;
 ENDSETS

 DATA:
! Import data from Excel;
  DMU = @OLE('\DOCUMENTS AND SETTINGS\GENERAL\DESKTOP\LINGO13\ADINDA\5VARA.XLSX', 'DMU');
  FACTOR = @OLE('\DOCUMENTS AND SETTINGS\GENERAL\DESKTOP\LINGO13\ADINDA\5VARA.XLSX', 'FACTOR');
  F = @OLE('\DOCUMENTS AND SETTINGS\GENERAL\DESKTOP\LINGO13\ADINDA\5VARA.XLSX', 'DATATABLE');

  NINPUTS = 5;  ! The first NINPUTS factors are inputs;

! Showing values in table format;
  @TEXT() = @TABLE(F);
  @TEXT() = @TABLE(W);

! Exporting data back to Excel;
  @OLE('\DOCUMENTS AND SETTINGS\GENERAL\DESKTOP\LINGO13\ADINDA\5VARA.XLSX', 'SCORE') = SCORE;

 ENDDATA
!------------------------------------------------------------;
! The Model;

! OBJECTIVE: Try to make everyone's score as high as possible;
  MIN = @SUM(DMU: SCORE);

! The LP for each DMU to get its score (OUTPUTS/INPUTS);
  @FOR(DMU(I):
   SCORE(I) = @SUM(FACTOR(J)|J #GT# NINPUTS:          ! SCORE(I) = @SUM(FACTOR(J)|J #GT# NINPUTS: F(I, J)* W(I, J)) /;
               F(I, J)* W(I, J));                     !            @SUM(FACTOR(J)| J #LE# NINPUTS: F(I, J)* W(I, J));
   ! Sum of inputs(denominator) = 1;
    @SUM(FACTOR(J)| J #LE# NINPUTS:
    F(I, J)* W(I, J)) = 1;
   ! Using DMU I's weights, no DMU can score better than 1;
   @FOR(DMU(K):
    @SUM(FACTOR(J)| J #LE# NINPUTS: F(K, J) * W(I, J))
     <= @SUM(FACTOR(J)| J #GT# NINPUTS:
      F(K, J) * W(I, J))
   );
  );

! The weights must be greater than zero;
  @FOR(DXF(I, J): @BND(0.00001, W, 100000));
  @FOR(DXF(I, J): @BND(0.00001, V, 100000));
END
```

## Appendix B: DEA Data

**Table 34 – DEA Data Analysis 1**

| Location | Seat Belt | | Road Safety | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | % Seat Belt Use Rear Seats | Road Density (km/1000 km^2) | Health Expenditure, total (% of GDP) | Number of Fatalities per Million Inhabitants | Fatalities per Million Passenger Cars |
| Australia | 97 | 92 | 104.6383 | 8.4780 | 77 | 141 |
| Austria | 89 | 49 | 1278.2401 | 10.1904 | 83 | 163 |
| Belgium | 79 | 46 | 5014.3465 | 9.6426 | 100 | 211 |
| Canada | 93 | 87 | 141.1163 | 10.0372 | 88 | 236 |
| Chile | 50 | 42 | 106.5063 | 6.8999 | 137 | 1269 |
| Cyprus | 81 | 9 | 1323.8919 | 6.0525 | 84 | 174 |
| Czech Republic | 90 | 80 | 1654.6596 | 6.5223 | 118 | 286 |
| Ecuador | 30 | 10 | 170.3397 | 6.9542 | 130 | 3422 |
| Estonia | 90 | 68 | 1272.7172 | 5.1007 | 146 | 375 |
| Finland | 89 | 80 | 233.1097 | 8.0445 | 72 | 153 |
| France | 98 | 83 | 1731.8688 | 11.0724 | 72 | 145 |
| Germany | 95.5 | 88 | 1803.9233 | 10.4711 | 60 | 120 |
| Greece | 75 | 42 | 883.8360 | 9.8276 | 148 | 334 |
| Hungary | 71 | 40 | 2103.8267 | 7.5603 | 123 | 408 |
| Iceland | 88 | 68 | 126.6796 | 9.3105 | 96 | 145 |
| Ireland | 86 | 63 | 1371.9124 | 7.6448 | 84 | 191 |
| Israel | 91 | 45 | 809.7870 | 7.4257 | 55 | 221 |
| Italy | 65 | 10 | 1640.1274 | 8.6378 | 95 | 163 |
| Japan | 93.5 | 12.5 | 3177.4614 | 8.1889 | 52 | 115 |

| Location | Seat Belt | | Road Safety | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | % Seat Belt Use Rear Seats | Road Density (km/1000 km^2) | Health Expenditure, total (% of GDP) | Number of Fatalities per Million Inhabitants | Fatalities per Million Passenger Cars |
| Latvia | 77 | 32 | 1079.5817 | 6.9793 | 179 | 449 |
| Malta | 96 | 21 | 9675.0000 | 8.6525 | 34 | 62 |
| Mauritius | 94 | 10 | 994.1176 | 5.1835 | 111 | 966 |
| Morocco | 75 | 19 | 129.3539 | 5.1729 | 124 | 2335 |
| Netherlands | 94 | 73 | 3261.1940 | 9.6814 | 48 | 107 |
| New Zealand | 95 | 87 | 350.1849 | 8.5306 | 100 | 163 |
| Norway | 93 | 85 | 287.0074 | 8.7460 | 49 | 108 |
| Oman | 95 | 1 | 157.9128 | 2.4663 | 312 | 1877 |
| Peru | 85 | 25 | 80.0540 | 5.0836 | 125 | 3279 |
| Poland | 74 | 45 | 1225.0643 | 6.4301 | 146 | 382 |
| Romania | 80 | 20 | 833.9989 | 5.2429 | 126 | 763 |
| Serbia | 55 | 4.5 | 443.4586 | 10.3589 | 130 | 652 |
| Spain | 50 | 69 | 1319.9517 | 8.4829 | 91 | 189 |
| Sweden | 96 | 90 | 948.3567 | 8.9172 | 51 | 111 |
| Switzerland | 86 | 61 | 1728.5368 | 10.6191 | 49 | 94 |
| United Kingdom | 91 | 87 | 1724.1041 | 8.4140 | 54 | 117 |
| United States | 82 | 76 | 673.6980 | 16.0549 | 142 | 314 |

**Table 35 – DEA Data Analysis 2**

| Location | Seat Belt | | Road Safety | | Trauma Management | Personal Safety | Traffic Safety |
|---|---|---|---|---|---|---|---|
| | % Seat Belt Use Front Seats | % Seat Belt Use Rear Seats | Road Density (km/1000 km^2) | Roads, paved (% of total roads) | Health Expenditure, total (% of GDP) | Number of Fatalities per Million Inhabitants | Fatalities per Million Passenger Cars |
| Australia | 97 | 92 | 104.6383 | 42.55 | 8.4780 | 77 | 141 |
| Austria | 89 | 49 | 1278.2401 | 100.00 | 10.1904 | 83 | 163 |
| Belgium | 79 | 46 | 5014.3465 | 78.20 | 9.6426 | 100 | 211 |
| Chile | 50 | 42 | 106.5063 | 21.43 | 6.8999 | 137 | 1269 |
| Cyprus | 81 | 9 | 1323.8919 | 64.04 | 6.0525 | 84 | 174 |
| Ecuador | 30 | 10 | 170.3397 | 14.82 | 6.9542 | 130 | 3422 |
| Estonia | 90 | 68 | 1272.7172 | 28.60 | 5.1007 | 146 | 375 |
| Finland | 89 | 80 | 233.1097 | 65.36 | 8.0445 | 72 | 153 |
| France | 98 | 83 | 1731.8688 | 100.00 | 11.0724 | 72 | 145 |
| Hungary | 71 | 40 | 2103.8267 | 37.72 | 7.5603 | 123 | 408 |
| Iceland | 88 | 68 | 126.6796 | 36.64 | 9.3105 | 96 | 145 |
| Ireland | 86 | 63 | 1371.9124 | 100.00 | 7.6448 | 84 | 191 |
| Israel | 91 | 45 | 809.7870 | 100.00 | 7.4257 | 55 | 221 |
| Japan | 93.5 | 12.5 | 3177.4614 | 79.60 | 8.1889 | 52 | 115 |
| Mauritius | 94 | 10 | 994.1176 | 98.03 | 5.1835 | 111 | 966 |
| Morocco | 75 | 19 | 129.3539 | 61.98 | 5.1729 | 124 | 2335 |
| New Zealand | 95 | 87 | 350.1849 | 65.41 | 8.5306 | 100 | 163 |
| Norway | 93 | 85 | 287.0074 | 80.45 | 8.7460 | 49 | 108 |
| Oman | 95 | 1 | 157.9128 | 41.25 | 2.4663 | 312 | 1877 |
| Poland | 74 | 45 | 1225.0643 | 67.59 | 6.4301 | 146 | 382 |
| Sweden | 96 | 90 | 948.3567 | 31.66 | 8.9172 | 51 | 111 |
| Switzerland | 86 | 61 | 1728.5368 | 100.00 | 10.6191 | 49 | 94 |
| United Kingdom | 91 | 87 | 1724.1041 | 100.00 | 8.4140 | 54 | 117 |
| United States | 82 | 76 | 673.6980 | 65.12 | 16.0549 | 142 | 314 |

## Appendix C: Definition of Fatality

**Table 36 – Definition of a Fatality**

| Country | Definition of Fatality | | | | | |
|---|---|---|---|---|---|---|
| | dead within 1 year of crash | dead within 30 days of crash | dead within 7 days of crash | dead within 24 hours of crash | dead at the scene | no specified period |
| Afghanistan | X | | | | | |
| Albania | | | | | X | |
| Angola | | | | | X | |
| Argentina | | | | | X | |
| Armenia | | | | | | X |
| Australia | | X | | | | |
| Austria | | X | | | | |
| Azerbaijan | | | X | | | |
| Bahamas, The | X* | | | | | |
| Bahrain | | | | | | X |
| Bangladesh | | | | | X | |
| Barbados | X | | | | | |
| Belarus | | X | | | | |
| Belgium | | X | | | | |
| Belize | X | | | | | |
| Benin | | | X | | | |
| Bhutan | | X | | | | |
| Bolivia | | | | | X | |
| Bosnia and Herzegovina | | X | | | X | |
| Botswana | X | | | | | |
| Brazil | X* | | | | | |
| British Virgin Islands | X* | | | | | |

| Country | Definition of Fatality | | | | | |
|---|---|---|---|---|---|---|
| | dead within 1 year of crash | dead within 30 days of crash | dead within 7 days of crash | dead within 24 hours of crash | dead at the scene | no specified period |
| Brunei Darussalam | | X | | | | |
| Bulgaria | | X | | | | |
| Burkina Faso | | | | | X | |
| Burundi | | | | | | X |
| Cambodia | | | X | | | |
| Cameroon | | | X | | | |
| Canada | | X | | | | |
| Cape Verde | | X | | | | |
| Central African Republic | X | | | | | |
| Chad | X | | | | | |
| Chile | X* | | | | | |
| China | | | X | | | |
| Colombia | | X | | | | |
| Comoros | | | | X | | |
| Congo, Dem. Rep. | | | | | X | |
| Congo, Rep. | X | | | | | |
| Cook Islands | | | | | X | |
| Costa Rica | X | | | | | |
| Croatia | | X | | | | |
| Cuba | X | | | | | |
| Cyprus | | X | | | | |
| Czech Republic | | X | | | | |
| Dominican Republic | | | | | X | |
| Ecuador | | | | X | | |
| Egypt, Arab Rep. | | | | | X | |
| El Salvador | | | | | | X |

| Country | Definition of Fatality | | | | | |
|---|---|---|---|---|---|---|
| | **dead within 1 year of crash** | **dead within 30 days of crash** | **dead within 7 days of crash** | **dead within 24 hours of crash** | **dead at the scene** | **no specified period** |
| Eritrea | X | | | | | |
| Estonia | | X | | | | |
| Ethiopia | X | | | | | |
| Fiji | | X | | | | |
| Finland | | X | | | | |
| France | | X | | | | |
| Gambia, The | X | | | | | |
| Georgia | | X** | | | | |
| Germany | | X | | | | |
| Ghana | | X | | | | |
| Greece | | X | | | | |
| Guatemala | | | | | X | |
| Guinea-Bissau | | | | | X | |
| Guyana | | | | | | X |
| Honduras | | | | X | | |
| Hungary | | X | | | | |
| Iceland | | X | | | | |
| India | | X | | | | |
| Indonesia | | X | | | | |
| Iran, Islamic Rep. | | X | | | | |
| Iraq | | | X | | | |
| Ireland | | X | | | | |
| Israel | | X | | | | |
| Italy | | X | | | | |
| Jamaica | | X | | | | |
| Japan | | X | | | | |

| Country | Definition of Fatality | | | | | |
|---|---|---|---|---|---|---|
| | dead within 1 year of crash | dead within 30 days of crash | dead within 7 days of crash | dead within 24 hours of crash | dead at the scene | no specified period |
| Jordan | | X | | | | |
| Kazakhstan | | | X | | | |
| Kenya | | | | | X | |
| Kiribati | | | X | | | |
| Korea, Rep. | | X | | | | |
| Kuwait | | X | | | | |
| Kyrgyz Republic | X | | | | | |
| Lao PDR | | | X | | | |
| Latvia | | X | | | | |
| Lebanon | | | X | | | |
| Lesotho | | X | | | | |
| Libya | | X | | | | |
| Lithuania | | X | | | | |
| Macedonia, FYR | | X | | | | |
| Madagascar | | | X | | | |
| Malawi | | X | | | | |
| Malaysia | | X | | | | |
| Maldives | | | | | X | |
| Mali | | | X | | | |
| Malta | | X | | | | |
| Marshall Islands | | | | X | | |
| Mauritania | | | | | X | |
| Mauritius | | X | | | | |
| Mexico | | | | | X | |
| Micronesia, Fed. Sts. | | | | X | | |
| Moldova | X | | | | | |

| Country | Definition of Fatality | | | | | |
|---|---|---|---|---|---|---|
| | dead within 1 year of crash | dead within 30 days of crash | dead within 7 days of crash | dead within 24 hours of crash | dead at the scene | no specified period |
| Mongolia | | | | | | X |
| Montenegro | | X | | | | |
| Morocco | | X | | | | |
| Mozambique | | | | X | | |
| Myanmar | | X | | | | |
| Namibia | | X | | | | |
| Nauru | | | | X | | |
| Nepal | | X*** | | | | |
| Netherlands | | X | | | | |
| New Zealand | | X | | | | |
| Nicaragua | | | | | | X |
| Niger | | | X | | | |
| Nigeria | X | | | | | |
| Norway | | X | | | | |
| Oman | | X | | | | |
| Pakistan | | | | | X**** | X**** |
| Palau | | | | | | X |
| Panama | | X | | | | |
| Papua New Guinea | | | | X | | |
| Paraguay | | | | | | X |
| Peru | | X | | | | |
| Philippines | | X | | | | |
| Poland | | X | | | | |
| Portugal | | | | | X | |
| Puerto Rico | | X | | | | |
| Qatar | | X | | | | |

| Country | Definition of Fatality | | | | | |
|---|---|---|---|---|---|---|
| | dead within 1 year of crash | dead within 30 days of crash | dead within 7 days of crash | dead within 24 hours of crash | dead at the scene | no specified period |
| Romania | | X | | | | |
| Russian Federation | | | X | | | |
| Rwanda | | X | | | | |
| Samoa | | | | | | X |
| San Marino | | X | | | | |
| Sao Tome and Principe | | X | | | | |
| Saudi Arabia | | X | | | | |
| Senegal | | | X | | | |
| Serbia | | X | | | | |
| Seychelles | | X | | | | |
| Sierra Leone | X* | | | | | |
| Singapore | | X | | | | |
| Slovak Republic | | | | X | | |
| Slovenia | | X | | | | |
| Solomon Islands | | | | | X | |
| South Africa | | | X | | | |
| Spain | | X | | | | |
| Sri Lanka | | X | | | | |
| St. Lucia | X | | | | | |
| St. Vincent and the Grenadines | X | | | | | |
| Sudan | | | | | | X |
| Suriname | | | | | | X |
| Swaziland | X | | | | | |
| Sweden | | X | | | | |
| Switzerland | | X | | | | |
| Syrian Arab Republic | | | | | X | |

| Country | Definition of Fatality | | | | | |
|---|---|---|---|---|---|---|
| | dead within 1 year of crash | dead within 30 days of crash | dead within 7 days of crash | dead within 24 hours of crash | dead at the scene | no specified period |
| Tajikistan | | X | | | | |
| Tanzania | | X | | | | |
| Thailand | | | | | X | |
| Timor-Leste | | | | | | X |
| Togo | | | | | X | |
| Tonga | X* | | | | | |
| Trinidad and Tobago | X | | | | | |
| Tunisia | | X | | | | |
| Turkey | | | | | X | |
| Turkmenistan | | | X | | | |
| Tuvalu | | | | X | | |
| Uganda | | X | | | | |
| Ukraine | | X | | | | |
| United Arab Emirates | | X | | | | |
| United Kingdom | | X | | | | |
| United States | | X | | | | |
| Uruguay | | X | | | | |
| Uzbekistan | | | | | X | |
| Vanuatu | X | | | | | |
| Venezuela, RB | X | | | | | |
| Vietnam | | | | X | | |
| West Bank and Gaza Strip | | X | | | | |
| Yemen, Rep. | | | X | | | |
| Zambia | | | | X | | |
| Zimbabwe | | | | X | | |

**Note**: X* = 1 year and 1 day, X** = 20 days, X*** = 35 days, X**** = dead at the scene or anytime after the crash