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ROAD TRANSPORT RESEARCH

ROAD SAFETY PRINCIPLES AND MODELS: REVIEW OF DESCRIPTIVE, PREDICTIVE, RISK AND ACCIDENT CONSEQUENCE MODELS

ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT

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FOREWORD

The Programme centres on road and road transport research, while taking into account the impacts of intermodal aspects on the road transport system as a whole. It is geared towards a technico-economic approach to solving key road transport issues identified by Member countries. The Programme has two main fields of activity:

- International research and policy assessments of road and road transport issues to provide scientific support for decisions by Member governments and international governmental organisations;

- Technology transfer and information exchange through two databases - the International Road Research Documentation (IRRD) scheme and the International Road Traffic and Accident Database (IRTAD).

Its mission is to:

- Enhance innovative research through international co-operation and networking;

- Undertake joint policy analyses and prepare technology reviews of critical road transport issues;

- Promote the exchange of scientific and technical information in the transport sector and contribute to road technology transfer in OECD Member and non-member countries.

The scientific and technical activities concern:

- Infrastructure research;

- Road traffic and intermodal transport;

- Environment/transport interactions;

- Traffic safety research;

- Strategic research planning.

ABSTRACT

IRRD NO. 892483

This research review was prepared by an OECD Scientific Expert Group. It is the sister report to the main publication *Road safety principles and models* (IRRD No. 888815). This document is targeted at road safety researchers. Four approaches to modelling for road safety research are discussed in depth: descriptive-, predictive-, risk-, accident consequence models. These approaches describes the state of the art and encourages further development and integration of these approaches, identifying areas where further research is needed.

Field Classification: accident studies

Field Codes: 80

Key Words: accident; statistics; theory; risk; mathematical model; analysis (math); forecast; accident rate; near miss; human factor; behaviour.

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EXECUTIVE SUMMARY

This report complements the OECD report *Road safety principles and models* and is targeted mainly at road safety researchers. The first report outlines the development of road safety during the course of the twentieth century, describes the need for a scientific approach to road safety research and details a systematic approach for road safety implementation. In this report, four approaches to accident modelling are treated in detail, outlining the main ways in which the road safety situation can be described and reviewing the models and theories currently used. The four approaches discussed are:

- Descriptive Models
- Predictive Models for Aggregated Data
- Risk Models for Non-Aggregated Data
- Accident Consequence Models.

Researchers are well aware of the importance of theories and models. They are often specialists in a specific field and probably have very little to learn in that particular area. However, the thinking and the advantages and disadvantages of various models used in other areas should be of interest to them.

DESCRIBING THE ROAD SAFETY SITUATION

An illustrative way to describe and model the road safety problem uses three dimensions: Exposure, accident risk and injury consequence. The magnitude of the problem is the product of these three factors. This model can be further expanded to a chain of ratios where the denominator in the last factor corresponds to the safety situation of interest. If the ratio is not available it can be estimated, however the price of such an estimation is a loss of accuracy.

The main accident and injury data sources are police reports, hospital and insurance company statistics. Each have their own advantages and disadvantages. To begin with none of them is complete as they all suffer from under-reporting. However they are generally incomplete in different ways which makes it interesting and often fruitful to use combinations of or comparisons between more than one source. For example, it is important to realise that if injuries are considered important to the research, the statistics should not only be based on police reports but also on hospital data. Underreporting is most pronounced for property damage only accidents and least for fatalities. Efforts should be made to co-ordinate the different sources so as to use the best from each of them.

The basic task in most road safety work is to describe the present situation – the magnitude of the road safety problem. It is easy and too common to focus exclusively on the number of accidents, injuries and fatalities which are the effects or consequences of the danger that characterise road traffic. However in order to be able to compare and rank road safety problems it is also necessary to find out the magnitude and character of the activities that generate the problems – the exposure.

Exposure measurements are unfortunately carried out much too seldom and not specifically for road safety purposes. There are several ways to measure exposure: Traffic counting (vehicle flow), travel habit surveys (samples of inhabitants), local exposure measurements (samples of places), and indirect exposure estimates (for example, fuel consumption). Various exposure units may be calculated. The most common ones are, number of inhabitants or registered vehicles, road-user or vehicle mileage, road-user or vehicle hours, number of trips, character of traffic situations.

Traffic conflict techniques can be used as a substitute for accident registration in analysis as well as for estimating exposure. This method is based on defining near accidents – conflicts – which are typically expressed as time to collision of the involved road users (for example less than 0.5 seconds). The advantage of this method is that data can be collected quite quickly. The disadvantage is that the validity is lower than for accidents. In order to estimate the number of accidents from conflict registration, ratios between the number of conflicts and accidents are used, which means that conflicts can also be regarded as a measurement of exposure as well as an indirect estimate of the number of accidents.

Road safety indicators are another even more indirect method to describe or study the road safety situation. These usually have to do with road user behaviour. The advantage is that they have an even higher frequency and are easier to collect than conflict data. The disadvantage is that their validity is normally even lower than that of the conflict technique.

Risk is the relationship between accidents on the one hand and exposure in terms of the magnitude of the activity on the other hand. As explained above, both accident and exposure measures may be expressed in a number of different ways. Risk is therefore a term that has to be used with care since it contains several pitfalls depending on which units are used, especially when comparisons are made.

Exposure and risk can also be estimated as an alternative to direct measurement. For example, by induced exposure, where the relative weights of both exposure and risk level are interpreted and estimated from accident data or by case control studies, where the risk is estimated directly by comparing samples with equal exposure.

Uncertainties or inaccuracies in traffic data used in describing the road safety situation often complicate the interpretation of the results. There are many causes to this unreliability which vary with the type of data source. Statistical methods are normally designed to cope with inaccuracies, however this is only true for inaccuracies which have a random character. Therefore inaccuracies caused by primarily systematic errors (bias) and spread components have to be compensated for in other ways.

There are many sources to these inaccuracies but the following three are the most common ones: Omission of entire records, simple inaccuracies due to misclassification, misjudgement or misprinting and delays in processing and recording information which may be different for different data. It is however possible to approximate and control the uncertainty of the ratios using certain methods, which are discussed further in Chapter I.

National accident, injury and fatality statistics are commonly used to make international comparisons. The OECD International Road Traffic Accident Database (IRTAD) makes this possible. It is however very difficult to draw more advanced conclusions from these comparisons since so many variables are not included in these statistics. It is recommended that more interest and resources are assigned to international comparisons and pooling of data on the road safety situation.

PREDICTIVE MODELS FOR AGGREGATED DATA (ANALYTICAL MACRO MODELS)

There are at least six major sets of independent variables behind changes in accident occurrence: External (for example, weather), socio-economic (for example, unemployment), transportation (for example, infrastructure), data collection (for example, accident reporting accuracy), sheer randomness and finally countermeasure intervention.

To eliminate the effects of the first four factors and to explain the effect of the systematic variable it is possible to use multivariate statistics (econometric modelling). Econometric methods which were originally developed for assessing complex economic relationships are in fact at least as well suited for accident analysis as they are for economics. Using these methods it is often possible to estimate the effect of a certain countermeasure. They may be viewed as a substitute for controlled experiments, which are often very difficult if not impossible to carry out.

Road accidents are random in a much more fundamental sense than most other events in society. They are the unintentional result of human behaviour, so it can never be predicted where, when and by whom a single accident is going to occur. Compelling arguments can be found to support the assertion that accident counts follow the Poisson probability law. The Poisson distribution has a number of useful properties. The most important one is that in a Poisson distribution the expected value and the variance are equal. Having estimated the former, we also know the latter. This fact may be used to enhance the efficiency of the econometric model to a degree not usually encountered in economic work.

Just as in controlled experiments, it is important that the analyst has a clear idea of what questions are to be answered and that the model is specified based on this knowledge when using multivariate statistics.

The most common functional form in multivariate statistics is the linear regression model, or generalisations thereof. The choice of regressors should primarily be based on the theory used, the question to be answered and the professional knowledge rather than the multiple correlation and curve-fitting ambition. The latter may lead to a nice fit of data but with results which have little value in terms of understanding and which are almost impossible to generalise outside the specific sample used. There are two main methods used for estimating the parameters in the model. These are the least squares method and the maximum likelihood method.

There are in principle two ways to evaluate the effectiveness of accident countermeasures:

- Predictive (cross-section and/or time-series) models
- Effectiveness evaluations (before-and-after studies)

The difference between these models is that the former is based on spatial variation and the latter on temporal variation. Both models have their advantages and disadvantages. The richest source of information are combined cross-section / time-series data sets.

RISK FACTOR MODELS - ANALYTICAL MODELS ON THE INDIVIDUAL (MICRO) LEVEL

The above section described in short how accident factors can be analysed by means of econometric models on the aggregated level. This could be characterised as a top- down approach. Another way to analyse the risk factors behind road accidents is to work from the individual level – on the driver- vehicle-road- level. This could be called a bottom-up approach. Here the purpose is to understand and be able to predict road user behaviour. Much of the individual risk problems seem to emanate from the increased complexity of the traffic situation. The more complex the situation, the greater the probability that some component in the system will fail.

An obvious problem is the lack of connection between the aggregated theories and models on the one hand and the individual theories and models on the other. There is a need for more theoretical and model work on the meta-level.

The individual approaches to risk factor modelling can be carried out within a number of different scientific disciplines -- such as psychology, sociology, ergonomics, medicine, biomechanics, physics. Overall, it is possible to separate between human factors models and technical models. This report focuses on the human factor models, which are less sophisticated and established than the statistical models described earlier.

Most of the risk models within these disciplines are what could be called sub-models since they focus on and only treat one limited aspect of the total road traffic situation. These models can have different purposes:

- To identify the risk factors.
- To quantify the risk factors.

In the initial phases of the development of human factor models, efforts were made to correlate accident involvement with various more permanent individual variables such as visual acuity, reaction time, personality. Some models designed to differentiate between good and bad (accident prone) drivers, contain a very large number of variables. Such models are almost impossible to interpret psychologically.

Action models are one major group of behavioural models and are based on road user task analysis, usually on one or more of the following variables:

- user disposition (suitability, qualification, capability);
- user assimilation (attitudes, assimilation of information, motor skills);
- user situation (routine situations, complex situations).

A generally accepted structure for action models is based on Rasmussen's hierarchical model differentiating between knowledge-, rule-, and skill-based errors and many researchers have developed this model further.

Another class of human factor models attempts to find relationships between accident involvement and more dynamic variables such as attitudes and various behaviours. These behaviour models can be classified into

- input-output (action) models;
- task analysis models (taxonomic);
- functional models (e.g. cognitive, motivational, adaptive, mechanical).

Behavioural risk models focus on how subjective risk is estimated and handled by road users and the resultant behaviour. These models study where the user problem is:

- In perceiving the risk.
- In accepting the risk.
- In controlling the risk.

For example, a frequently discussed behavioural risk model in road safety research is Wilde's risk homeostasis model. It is a model relating risk perception to risk acceptance.

The vehicle (e.g. size, brakes, stability), the road (e.g. geometry, surface, intersections), and the traffic (e.g. volume, speed, gaps) may be considered as situational stimuli to driver behaviour. Technical risk models study user behaviour and risk in specific physical situations of these types. For example, vehicular models deal with accident involvement and driver behaviour as a function of vehicle characteristics such as size, stability, braking performance. Infrastructural models deal with driver behaviour and accident risk as a function of road design (e.g. geometry, width, surface, intersection, obstacles). Traffic models deal with driver behaviour and accident rate as a function of traffic characteristics (e.g. volume, speed and speed distribution, homogeneity, gap distribution). Most of these models are on the aggregated level and very few focus on the individual driver.

APPLYING ACCIDENT CONSEQUENCE MODELS

The consequences of road traffic accidents can be described in different terms. Historically of course, they have been viewed as a road safety problem with the description based on fatalities and injuries. Another more interesting way is to view them as a public health problem with the description based on the seriousness of the consequence of each victim (for example, the Abbreviated Injury Scale – AIS) or the loss of health for instance in terms of time spent in hospital or away from work. Finally the consequences may be described in economic terms such as medical costs, rehabilitation costs, loss of production costs, human costs, damage to property costs and administration costs.

Of the three basic variables that describe the road safety situation, exposure, accident risk and injury consequence, the latter has been the most successfully modified over the last few decades. One of the main reasons is that compensatory reactions from the users (see risk models above) are not so pronounced for countermeasures aimed at accident consequence reduction as for countermeasures aimed at accident risk reduction.

Injury consequences of road accidents can be reduced in many ways for example, by changes in the environment, vehicles, the use of protective devices, driver behaviour, rescue procedures, treatment and rehabilitation routines. There are in principle two ways to study the consequences of (losses due to) accidents:

- On the aggregated level using statistical methods.
- On the individual level using case studies, experiments or simulations.

There are many factors that influence the consequences of accidents. Many of these influences have been modelled and quantified. The main factors are:

- Type and age of traffic element (user/vehicle) involved in the accident.
- Accident manoeuvre type (overtaking, crossing, reverse, turn).

- Speed (injury accident risk changes with the second power, serious injury accidents with the third power and the fatal accidents with the fourth power of relative change of speed).
- Mass of the car (the risk for driver fatality in a collision between a 900 kg car and an 1800 kg car is about ten times higher for the driver of the lighter car).
- Other factors are road design, road side design, age, model and design of the car, use of protective equipment such as belts and helmets.
- Use of alcohol and drugs

There are various ways to describe the injury level. One classification scheme is the International Classification of Diseases (ICD). This describes the type of injury and its location but not its severity, which is a very important variable. The most common injury severity scale is the Abbreviated Injury Scale (AIS). This scale goes from 1: minor injury to 6: maximum injury. In cases where there are multiple injuries, another scale is used – the Injury Severity Score (ISS). This scale indicates the severity in terms of long term disability and goes from 0: no long term impairment to 6: life time serious impairment.

Biomechanical models have mainly developed through experiments and simulated collisions. These models are important because they facilitate the detection, understanding and prevention of serious injuries. For example neck injuries were not observed for a long time although it is now known that they constitute a serious health problem. Biomechanical models helped to detect and understand this type of injury. Today, knowledge of biomechanics is very advanced. The human body can be simulated for most of the common collisions and the injuries caused can be studied using computers.

CHAPTER I MODELS DESCRIBING THE ROAD SAFETY SITUATION

Accident data is the basis for analysing and describing traffic safety problems. How this data is used and presented will affect the way problems are interpreted. In order to compare and rank different traffic safety problems, the key information is the exposure. In this chapter an overview of the many sources of traffic data is given and the problems associated with these sources and the inaccuracies that occur in the collection of data are discussed. Methods of analysing available accident, injury and exposure data are presented, which allow comparisons and relevant descriptions of different traffic safety problems.

I.1. SAFETY DATA AND INDICATORS

The road safety situation ought to be described in different dimensions related to:

- Road users – transportation mode, age, gender.
- Vehicles – different types of vehicles, speed.
- Roads – streets, two-lane roads, motorways, speed limit.
- Trips – purpose of travelling, trip distance, travel time.

Generally, there are two main information sources used in traffic safety analysis:

1) Accident and/or casualty data.
2) Exposure data.

Calculations or estimates of risk situations can be done using these two types of data collected for the same category and time period.

I.1.1. Accident and/or casualty data

There are several sources of accident data:

- Official accident registration by the police as the main source,

and several alternative sources:

- Insurance company data: Only accidents involving insured vehicles.
- Hospital data: Only persons (patients) injured in road accidents at hospitals.
- Accident involvement surveys and other self-reporting data.

All sources have their advantages and disadvantages. It has to be stressed that these alternative databases are usually set up for different purposes than traffic safety.

Police registration itself is not done entirely for traffic safety purposes. This, together with police workload issues, results in major flaws in police registration. The notification of an accident to the police is probably the step in which most information is lost. Many small accidents can be handled by the conflicting parties. If the damage is small, not even the insurance companies are informed as a result of no-claims bonuses. This results in a strong tendency to report more serious (damage) accidents leading to a bias where certain types of accident are more likely to be absent from data bases than others.

It should be noted that the police are police professionals and not medical or engineering experts, so some information in the accident record, particularly on accident severity and causes may not be very accurate, as has been shown in comparisons of hospital and police data (Rosman, 1994). It is very clear that the more serious the injury, the more likely it is to be registered by the police. This is illustrated by estimations in the Netherlands shown in Table I.1 (Harris, 1990).

Table I.1. **Overview 1994 in the Netherlands**

Severity	Police	Total number	%
Deaths	1 300	1 300	100
In-Patients	12 000	23 000	52
Out-Patients	19 000	145 000	13
Not Hosp.-Treated	18 000	472 000	4
TOTAL	**50 300**	**640 000**	**8**

Similar patterns for the estimated values tabled above, occur in other countries. Another report by Hakkert and Hauer (1988) states that approximately 2% to 10% of the injured die as a result of the accident after the 30 days limit normally used for attributing the cause of death. These differences in definitions are likely to cause differences in data sources.

The table above only concerns casualties in **injury accidents**. Registration of **non-injury accidents** (Material Damage Only Accidents**)** by the police is, not surprisingly having seen the above table, even less complete than that of accidents with victims who need treatment.

Alternative sources such as insurance company data, hospital data, accident survey data and other self reporting data are often used to assess the level of underreporting in police data (Hakkert and Hauer, 1988). In general, those sources provide information on only part of the safety problem; hospital data only offer information on hospitalised victims and fatalities, public surveys only offer information on the respondents which has to be generalised to the entire population. Insurance companies should be able to produce information on damage and injuries in reported traffic accidents.

As a rule, alternative sources have alternative purposes and the information gathered from those sources is likely to be optimal for its purpose but this does not mean it is optimal for traffic safety analysis purposes. It is important to take note of biases that are therefore inherent and can also vary between countries. For example, the reporting of non-injury accidents to insurance companies may vary according to legislation in different countries. Policies also vary between insurance companies and hence no single company can provide a representative sample of a regions road safety problems (OECD 1990).

I.1.2. Exposure data

Although accident (casualty) reporting data is the basic information needed for road safety analysis, it is exposure data which is the key information. Exposure can be described in different ways, for example, involved units, distance travelled, time spent in traffic, number of trips or traffic situations related to different accident types. The most common exposure units are:

- Inhabitants
- Registered vehicles
- Vehicle (driver) mileage
- Road user mileage
- Vehicle (driver) hours
- Road user hours
- Number of trips
- Traffic situations

Exposure data is not usually collected for safety purposes but for road and transport (economic) planning procedures. Two main methods are used at national levels: Traffic counting systems or travel habit surveys. Additional exposure investigations in local areas and site observation systems to collect data on road user behaviour are also common. The systems can be more or less representative for the national situation.

Traffic counting systems

Almost all industrial countries have a traffic counting system for their main roads estimating the annual average daily traffic (AADT) on different road sections. The data is mainly used for the national road planning system. The limitation of traffic counting systems is that the vehicle types can be identified but not the occupants. Vehicle (driver) kilometrage can be estimated from these counts and hence the safety for different road sections can be determined by calculating accident (injury) rates -- the number of accidents (injured) per (million) vehicle kilometres. The accident (injury) rate can be calculated for single years or periods of years; for single sections or groups of sections of the same road and traffic standard. For example motorway sections with a specific speed limit and vehicle flow more than x vehicles per day for the years 19xx-19yy.

Travel habit surveys or vehicle use surveys

The other way of collecting exposure data is to survey samples of inhabitants or vehicle owners about their travel habits or use of their vehicle for selected time periods. From this information, person kilometres, vehicle kilometres, travel time and number of trips for aggregated time periods can be estimated for different transportation modes or vehicles. *From these estimates of exposure, the total exposure is the product of the registered population or number of vehicles and the average estimated exposure for the individual of different groups of road users or vehicles:* The limitation of travel surveys is that it is difficult to relate the distance travelled to the route taken.

Total Exposure = (Population) x (Average Estimated Exposure)

or

Total Exposure = (Number of Vehicles) x (Average Estimated Exposure)

For example it is possible to estimate the exposure of passenger cars with male drivers of a specific age group in time and relate this to the number of injured male drivers of passenger cars in the same age group from reported accidents (police) or casualties (police or hospitals).

Indirect exposure estimates

Information on the use of petrol and diesel in the transport sector is, due to taxation and delivery statistics, normally available on national or regional levels. This is often a good indicator of the use of passenger cars as they consume the majority of the petrol in society and the average consumption per vehicle mileage is normally known. Factors that need to be taken into account when using this information range from monitoring the development of more fuel efficient vehicles, to monitoring outdoor temperatures which have an effect on fuel consumption of vehicles.

I.1.3. Traffic conflicts

Traffic conflict techniques (Hydén, 1987) can be used as a substitute for accident registration in analysis as well as for estimating exposure. Conflicts (near accidents) occur far more frequently in traffic and can include the whole range of incidences where the actual accident is just at one end of the scale. Techniques range from the purely subjective -- no quantifying measures but using descriptions such as “sudden behaviour” or “evasive action” -- to the more objective where conflicts are rated by measurements such as “time to collision” (if no evasive is action taken) or “post-encroachment time” (time between one user leaving the potential collision point and the other road user entering the point). Conflict studies are often combined with other types of behavioural studies.

In order to estimate the number of accidents from conflict registration, ratios between the number of conflicts and accidents are used, which means that conflicts can also be regarded as a measurement of exposure as well as an indirect estimate of the number of accidents.

At specific locations, normally intersections, observation or video-recording methods are used to estimate exposure data based on the number of vehicles or pedestrians using the area. The exposure data can also be based on traffic situations, either registered accidents or using traffic conflict techniques for the area. Combined with traffic counting systems, the accident rate or conflict rate can be expressed as the number of accidents (or conflicts) per (million) vehicles entering the intersection.

Advantages of using conflict techniques are that short term observations produce much higher numbers of conflicts than accidents and the severity can be rated. The disadvantages are that it is time consuming to observe the traffic in order to build up enough data and the observers have to be trained.

I.1.4. Risk

Accident/fatality rates

The concept of risk is a ratio of accidents/casualties and some measurement or estimate of the exposure (the existence of the units or the magnitude of the activity involved in the accidents) and can be referred to as accident/casualty rates.

Induced risk and exposure

From accident statistics, the concept of induced exposure was developed. The problem with this technique is that the risk level is also induced at the same time, which means two indirect values to interpret, where the product of the induced exposure and the induced risk is the number of accidents for the group of interest.

Number of Accidents = (Induced Exposure) x (Induced Risk)

The question is, how can accident data be used to estimate the magnitude of exposure for different road user groups involved in accidents? Many efforts have been made to create statistical models which express the number of accidents for a group of drivers or traffic elements as a product of a risk factor (accident liability) and an accident exposure factor. The basis is normally a matrix describing the occurrence of different groups of vehicles, drivers, or injured in accidents.

Table I.2. **Matrix of accidents for different road users**

	Basic information	**Involved in collisions with**		
		Group 1	**Group 2**	**Group 3**
Group 1	y_1	x_{11}	x_{12}	x_{13}
Group 2	y_2	x_{21}	x_{22}	x_{23}
Group 3	y_3	x_{31}	x_{32}	x_{33}

The basic information (y_1, y_2, y_3) can be for example, the number of single accidents in the group, or the proportion of "innocent drivers" among the drivers involved in accidents.

The next step is to give a model for the x_{ij}'s including risk and exposure factors. The most common is:

$$y = r_i e_i$$
$$x_{ij} = r_i r_j e_i e_j$$

where **r** are risk factors and **e** exposure factors.

The general assumption is that the different groups are not separated from each other in the road system. An example using fatalities in traffic in Sweden 1991-1993 for accidents involving only passenger cars and lorries is given in Box I.1. Information about which vehicle the fatality occurred is also given.

Although the values in the example in Box I.1 show a high relative risk of being killed in accidents involving lorries, or that it is rather safe to be a lorry occupant in a collision with a passenger car, it is difficult to interpret or quantify the figures due to all the assumptions which must be made. The concept of induced exposure was created at the beginning of interest in safety studies and before sampling methods were used to estimate mileage exposure. Today the mileage exposure is more or less known for different road user or vehicle groups, however, in order to distribute this total exposure for subgroups – for example, age groups of drivers – different methods of induced exposure may be of interest.

Case control studies

Case control studies are another way of identifying the risk of two different conditions, resulting in an odds ratio. They are common in health research. The comparisons are based on the fact that these conditions have different influences on the risk of an accident and the existence of the conditions is registered for traffic elements not involved in accidents at the corresponding time and space. The method can be used in cases when the methodology is close to a risk evaluation based on aggregated data concerning accidents and exposure. The problem is that the accident occurrence cannot be proved to be correlated with the defined "risky" condition. The case control study method has been used in order to identify vehicle factors contributing to accidents and requires field investigations.

Box I.1. **Example of induced risk or exposure**

Table I.3. **Number of fatalities in passenger cars and lorries**

	Single vehicle collision	**Collisions with**	
Killed in		**Passenger car**	**Lorry**
Passenger car	727	528	285
Lorry	42	11	24

The basic information is the distribution of fatalities in single accidents in passenger cars and lorries. The simplest assumption is that this is proportional to the exposure (mileage). Passenger car occupants "travel" 17.3 times more than lorry occupants – hence exposure unit for lorries is 1 and for cars is 17.3. Using the above matrix, and using a risk factor of one for each type of collision, the fatality risk of being killed in collisions with passenger cars is 1.76:

$$\mathbf{r}\ (\text{risk}) = \left(\frac{x_{ij}}{e_i e_j}\right) = \left(\frac{528}{17.3 \times 17.3}\right) = 1.76$$

Likewise, the fatality risk of a car passenger in a collision with a lorry is 16.47, a lorry occupant in a collision with a passenger car 0.64 and a lorry passenger in a collision between lorries is 24. These values have no dimensions but provide a basis for comparison.

Relative risk

Sometimes the level of exposure is not known but the proportions of the total exposure can be estimated and compared with the corresponding proportions of accident or casualty statistics. This can result in the expression that a specific group in traffic is over-represented in accidents compared to its proportion in traffic.

Normal national presentations are the number of injured (fatalities) per inhabitants for different age groups. This is an example of a risk description which is both relative and exposure oriented (years of life). This is also the normal definition of health risk level, which can be compared with other health problems resulting in fatalities (mortality rate) or casualties.

Sometimes the casualty information is transformed into monetary values, loss of (life) time or other aggregated units to achieve more accurate health risk comparisons.

Risk and consequence

The concept of risk has many dimensions, for example, the probability of being involved in an accident, the probability of being injured in an accident or the probability of being killed or severely injured in an accident. These dimensions can be expressed by a chain of probabilities in theory and of ratios in practice. This chain of conditional probabilities (ratios) expressed in rates, casualties per accident and proportions can be used to describe and evaluate the traffic safety situation in several dimensions.

I.2. SAFETY PROBLEM ANALYSIS

I.2.1. A descriptive approach

A road safety problem can be described in three principal dimensions. The first dimension is the magnitude of the activity which results in accidents – the exposure. The second dimension is the accident (injury) risk situation for accidents (injuries) and the third dimension is the accident (injury) consequences. These three dimensions **exposure**, **risk** and **consequence** cover the three main effects on safety: Changes in any one of these dimensions, will change the entire safety situation.

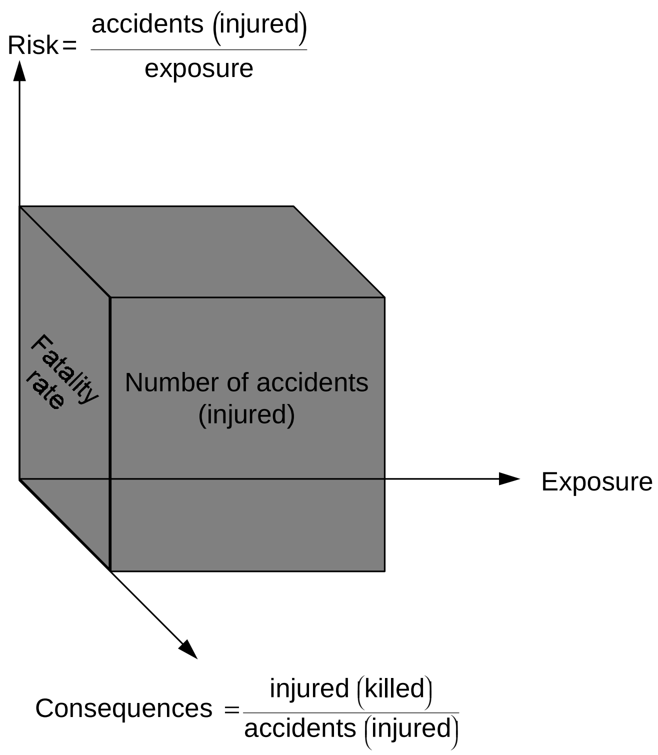
$$\text{The Traffic Safety Problem} = \text{Exposure} \times \text{Risk} \times \text{Consequence}$$

An example of this expression is:

$$Fatalities = (Exposure) \times \left(\frac{Accidents}{Exposure} \right) \times \left(\frac{Fatalities}{Accidents} \right)$$

The two last factors describe the accident rate and the fatality consequence per accident. Together they result in the fatality rate (fatalities per exposure). See Figure I.1, where the volume is proportional to the number injured, the area of the side face is proportional to the number of fatalities.

Figure I.1. $\textbf{The Traffic Safety Problem} = \textbf{Exposure} \times \textbf{Risk} \times \textbf{Consequence}$ **.**



This can be transformed to the mortality rate, which is the number of fatalities related to the number of inhabitants as a product-chain consisting of the estimate of the average exposure per inhabitant, the accident rate and the average number of fatalities in an accident.

$$\left(\frac{Fatalities}{Inhabitants}\right)=\left(\frac{Exposure}{Inhabitants}\right)\times\left(\frac{Accidents}{Exposure}\right)\times\left(\frac{Fatalities}{Accidents}\right)$$

The theory is illustrated in Figure I.2 presenting the safety situation in another 3-dimensional way for different transportation modes in Sweden. The accident data is the average annual fatalities and injuries for the years 1990-1992 and the exposure data is the estimated person kilometres in 1992. The volumes are proportional to the number of fatalities given inside the brackets. The height is the total injured per million person kilometres – the risk – and the width is proportional to the exposure for different transportation modes. The depth is the probability of being killed if injured – the number of fatalities of all injured. The front areas are proportional to the number of injured and the side areas are proportional to the fatality rate, – fatalities per million person kilometres.

Figure I.2. **The traffic safety situation - Average number of killed annually for different transportation modes in Sweden 1990-1992**

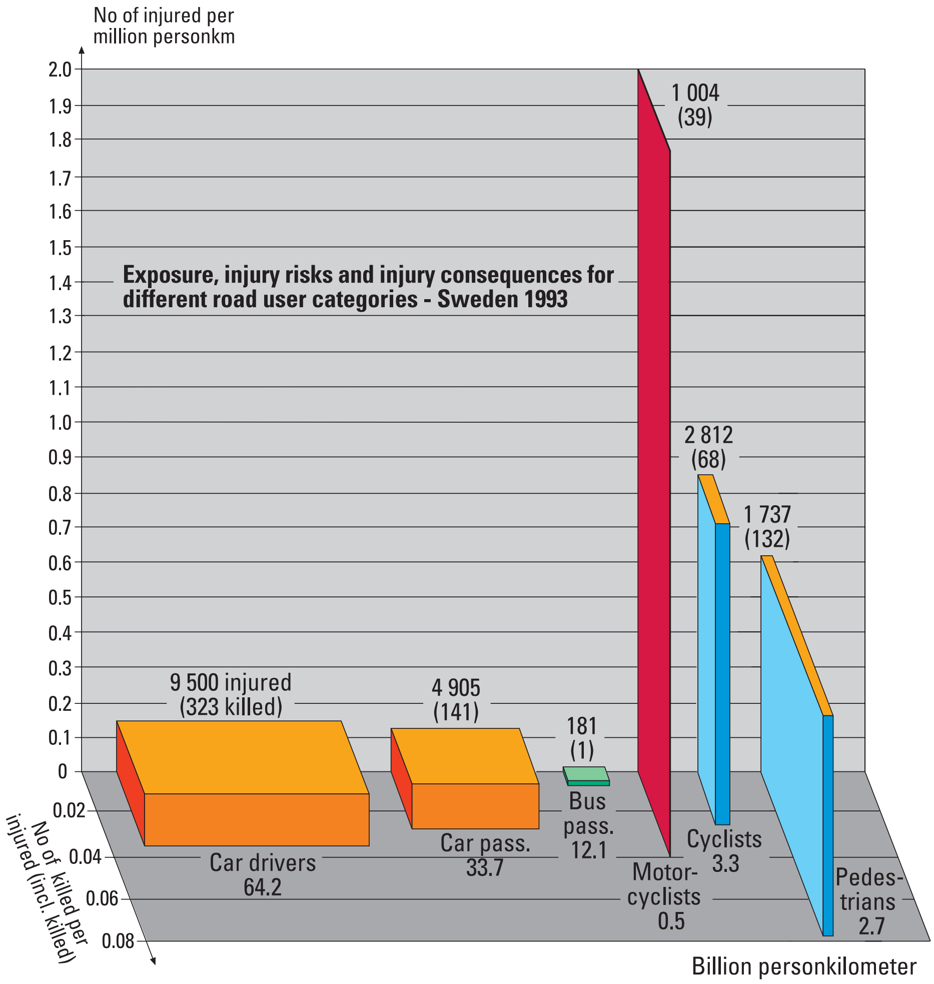
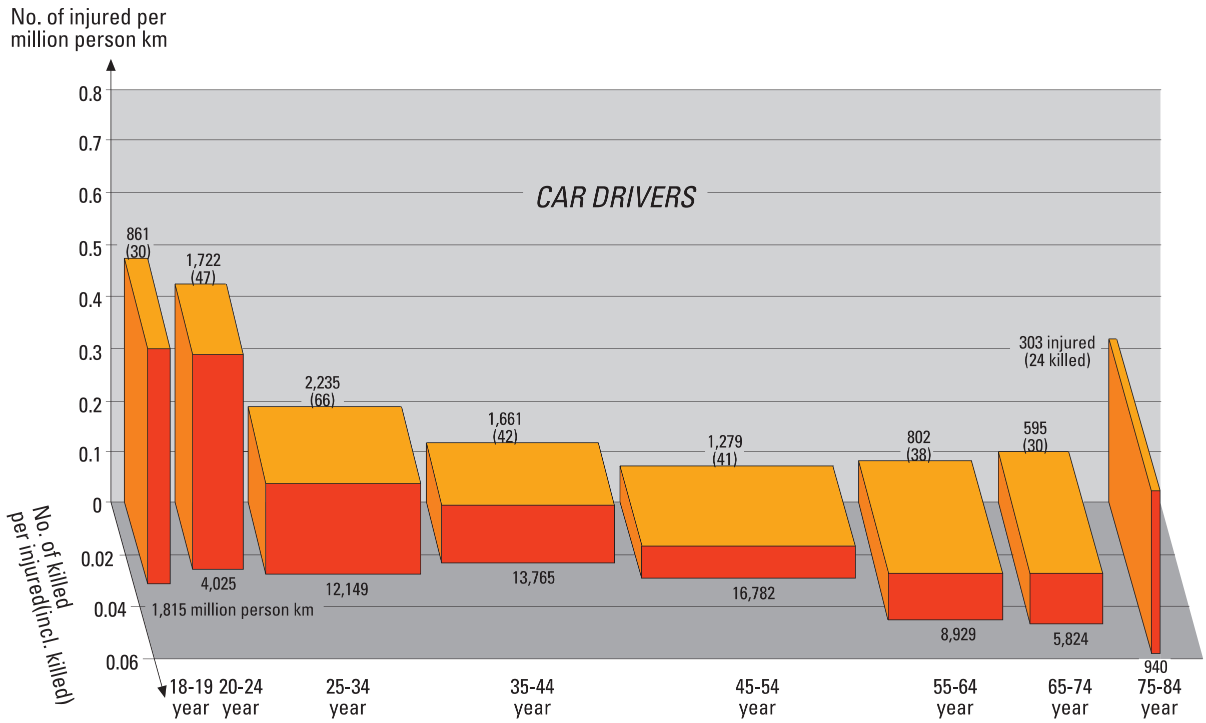


Figure I.3 based on ratio chain decomposition for car drivers and age groups in Sweden (Thulin and Nilsson, 1994) illustrates some of the possibilities for describing a traffic safety problem and creates a basis for comparisons.

Figure I.3. **The traffic safety situation - Annual number of killed car drivers in different age groups in Sweden 1990-1992**



I.2.2. Interpretation and reliability

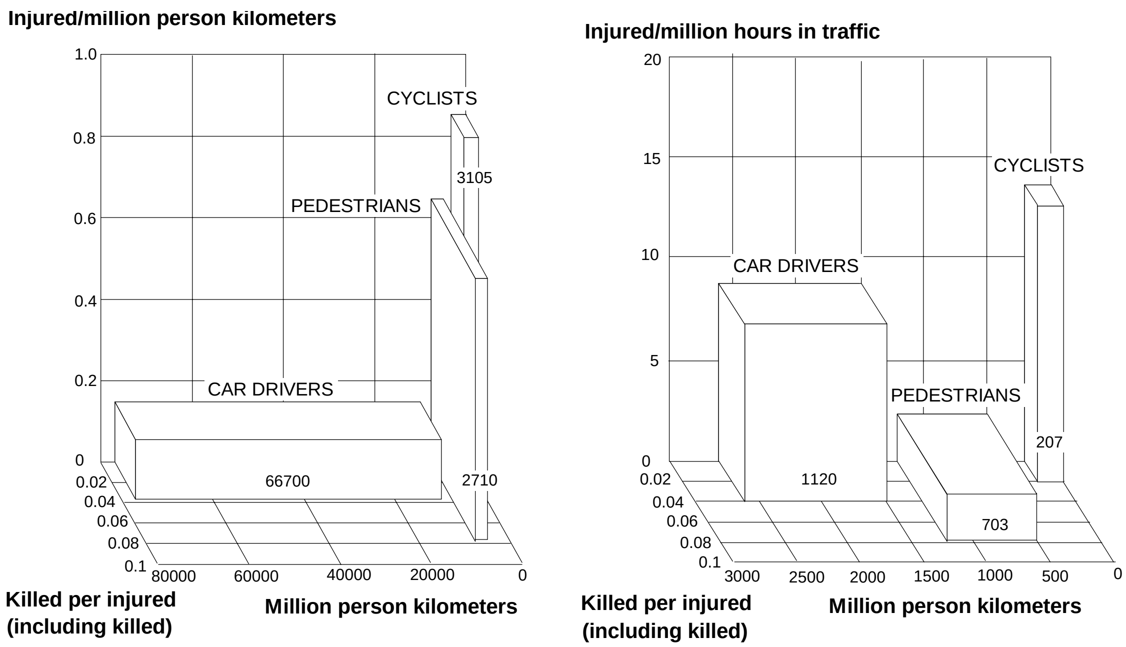
Just studying accident, casualty or fatality figures will give very little information on the changes in exposure, different terms of risks or consequences, thus giving no indication what measures are most important in order to improve the safety situation. Exposure is the key information required to describe and compare safety situations or problems. However, the choice of exposure measurements used, results in different descriptions of the risk situation. This is highlighted by Figure I.4 where the risk is described using two different measures of exposure: The number of injured per million person-kilometres and the number of injured per million-hours in traffic for car drivers, cyclists and pedestrians.

The number of injuries and fatalities is of course the same (the front areas and the volumes in the figure) as are the number of fatalities per injuries (the depth of the graphs). However, using the two different exposure measures, the description of the risk situations among these three transportation modes will change. If the exposure is measured in person kilometres, car drivers are at a lower risk than pedestrians and cyclists. If the exposure is measured in hours in traffic, the risk of being injured as a pedestrian is lower than for car drivers and cyclists.

A third possibility is to use the number of trips as the exposure unit. In this case the risk will correspond very closely to the figure using hours in traffic as the exposure unit, since the average travel time per trip is more or less independent of the travel modes presented.

When extensive comparisons are made between transportation modes, person-kilometres is the preferred exposure unit. However for comparisons of risks with other activities in society – for example, between traffic accident risk and accident risk in the work place for different sectors – time is the usual exposure unit used.

Figure I.4. **Risk description using different exposure units, person kilometres or hours in traffic, for car drivers, pedestrians and cyclists, Sweden 1992**



Interpretation problems often occur due to uncertainty or inaccuracy in the traffic safety analysis data. These inaccuracies can have many causes.

Data is in most cases based on accident information and the sources themselves have some limitations to start with. The two main problems concerning accident data are “underreporting” and “misclassification” as discussed in Section I.1. At a secondary level, the time lag between the reporting and registration of accidents may also cause problems concerning the interpretation of time-series or before and after studies. One way to control for this is to compare different data sources, but in reality there is no “true” reference.

Exposure data used in accident analysis does not always correspond to the accident period or the accident group under investigation, as the exposure collection is valid for a given time period or a given date (for example, for population or car fleet). There is rarely a total correspondence in time, space and road user group between accidents and exposure. While accident data is collected continuously and stored in databases, exposure data is often collected with random selections of observation units in time and space and results in estimates of different accuracy. Assumptions about accident distributions and the accuracy of exposure estimates can be analysed using statistical methods and significance tests of the results can be expressed.

This will not solve the hidden interpretation problems. In order to resolve these problems the researcher must have an in-depth knowledge of the data used and be able to show how these problems influence the results. There is no final recommendation how to solve these problems. Increased knowledge and research are needed to avoid mistakes in the interpretation of the results. Particular areas that need improving are control activities, comparing data from different sources and methods of collecting exposure data.

The number of traffic fatalities per population when comparing different countries, is one illustrative example of an interpretation problem. In most countries the recorded fatalities include visitors to the country, the definition of fatalities that occur within 30 days of the accident are recorded differently in different countries, as are suspected suicides or natural deaths. The population is presented for the last day of the year and offers no information of inhabitants staying abroad (or in jail) for different periods during the year.

Even if each interpretation problem has only a minor influence on the comparisons, the comparisons at the total level should always be discussed.

I.3. RATIO ESTIMATES

I.3.1. Uncertainty of ratios

In the discussion above, it can be seen that a number of traffic unsafety characteristics are defined as ratios of certain quantities (for example, the number of fatalities per billion vehicle kilometres). If such a ratio is to be compared with other ratios, it must be realised that such ratios are estimates. This section is devoted to the calculation of the uncertainty of ratios due to statistical errors. Better approximations may exist but those methods require detailed statistical information on the distributions of both components. The method described below assumes that only basic statistical information is available, notably the expected values of X=E(X) and Y=E(Y) together with their respective variances VAR(X) and VAR(Y) and their mutual covariance COV(X,Y). This may be sufficient if normal distributions are assumed for X and Y, but it is generally not sufficient for the ratio.

A ratio R=X/Y is considered. One of the least complex examples is the number of fatalities per inhabitant of a country. The latter figure can be determined quite accurately in many countries and the error in this number is sometimes ignored. Assuming such action to be acceptable, this yields:

$$\mathrm{E}(\mathrm{Y}) = \mathrm{Y}, \quad \mathrm{VAR}(\mathrm{Y}) = 0 \quad \text{and} \quad \mathrm{COV}(\mathrm{X},\mathrm{Y}) = 0,$$

$$\mathrm{VAR}(\mathrm{R}) = \frac{\mathrm{VAR}(\mathrm{X})}{(\mathrm{E}(\mathrm{Y}))^2}$$

The variance of the ratio is thus proportional to the variance of the numerator X. In many cases this is an acceptable approximation of the variance of the error. Unfortunately, it is often applied in cases where it may not be a very good approximation.

The next step is to linearly approximate the ratio. This type of approximation involves both expected values and variances and covariances as well. However in this context it may be assumed that X and Y are uncorrelated. The fundamental assumption in this step is that the linear approximation is good enough in the area in which X and Y are statistically distributed. The smaller the statistical variation of X and Y, the better the approximation. Many textbooks offer a proof, e.g. Rice (1995, p 153):

$$\mathrm{R}^* = \frac{\mathrm{E}(\mathrm{X})}{\mathrm{E}(\mathrm{Y})}$$

$$\mathrm{VAR(R)} = \left(\frac{1}{\mathrm{E(Y)}}\right)^2 \ \mathrm{VAR(X)} \ + \ \left(\frac{1}{\mathrm{E(Y)}}\right)^2 \ \mathrm{VAR(Y)(R\,*)^2}$$

The variance of R becomes smaller than the simple estimate ignoring the variance of Y. One important observation in the above is the definition of R^*. It is defined as the ratio between the expected values of X and Y. It should be noted that E(Y/X) ≠E(Y)/E(X) in general. Using the variances and expected values, this difference, called bias, can be estimated. It can be found (Rice, 1995, p 153):

$$\mathrm{E}\left(\frac{\mathrm{X}}{\mathrm{Y}}\right) \ \approx \ \mathrm{R\,*} \ + \ \left(\frac{1}{\mathrm{E(Y)}}\right)^2 \ \mathrm{VAR(Y)\ (R\,*)}$$

In the case of traffic safety, R^* is usually positive, so it can be seen that the bias is larger when the variance of Y is larger. Summarising, there are two errors that result from neglecting the variance of the denominator:

bias in expected value: $\left(\frac{1}{\mathrm{E(Y)}}\right)^2 \left(\mathrm{VAR(Y)(R\,*)}\right)$; bias in variance: $\left(\frac{1}{\mathrm{E(Y)}}\right)^2 \left(\mathrm{VAR(Y)(R\,*)^2}\right)$

Box I.2. **Example using ratios**

In 1992, the number of killed persons on mopeds in the Netherlands was 105. According to a survey, the number of person kilometres was 1173.50 million kilometres. Assuming no error in the vehicle kilometres, the ratio of killed moped travellers per million kilometres is about 0.089 ± 0.017 if VAR(X)=X (the number of killed persons is Poisson distributed). Including an error variance of exposure, VAR(Y)= 8247.89 gives, (1173.50 ± 178 million kilometres)

the variance of R , VAR(R) ≈ 0.000124

1.96 Sqrt(0.000124)=0.0218. So in fact the ratio is in the interval 0.090±0.022, instead of 0.089± 0.017

Table I.4. **Accidents in The Netherlands**

	R^* %	R	Bias(R) %	Confidence interval		
				Denom.	**Denom. and Nom.**	**Bias %**
All	0.0077	0.0077	0.0173	0.0004	0.0005	10.5612
Walking	0.0385	0.0386	0.0466	0.0061	0.0063	3.4780
Car (driver)	0.0053	0.0053	0.0333	0.0005	0.0005	6.8454
Car (passenger)	0.0053	0.0053	0.0888	0.0007	0.0008	8.5543
Bicycle	0.0174	0.0174	0.0432	0.0022	0.0023	5.2767
Moped	**0.0895**	**0.0900**	**0.5989**	**0.0171**	**0.0218**	**27.6275**
Motor/scooter	0.1028	0.1055	2.6377	0.0209	0.0388	*85.8243*
Bus	0.0003	0.0003	0.1711	0.0002	0.0002	0.5972
Other	0.0019	0.0020	3.6483	0.0037	0.0038	1.8078

From the table it can be inferred that the bias in the ratio is small (max. 3.6 %) compared to the bias in the confidence interval (1.96 standard deviation) estimate (max. 85%).

I.3.2. Control and interpolation of ratios

Sometimes one of the required ratios is not available or ought to be controlled. In the example above concerning the exposure we can assume that the annual passenger car kilometrage per passenger car is not known, but estimates of the other ratios and number of inhabitants exist. If we use Sweden as an example this ratio can be calculated or controlled against existing information on the use of passenger cars: 92.7 billion person kilometres with passenger cars 1992 from a travel habit survey.

$$8.7 \times 10^{6} \ (\text{inhabitants}) \times 0.412 \left(\frac{\text{passenger cars}}{\text{inhabitants}} \right) \times \mathbf{n} \left(\frac{\text{passenger car km}}{\text{passenger cars}} \right) \times 1.587 \left(\frac{\text{person km}}{\text{passenger car km}} \right)$$
$$= 9.27 \times 10^{10} \ \text{person kilometers}$$

Annual passenger-car-km/passenger-car: **n** = 16,297 kilometres

This calculation of passenger-car-kilometrage is higher than existing estimates, which are less than 15,000 kilometres/year (from direct or indirect observations of mileometers in samples of cars). If this is accurate the average number of person-km per passenger-car-km and/or the number of passenger-cars per inhabitant is underestimated. Another interpretation is that the person-kilometres are overestimated.

It is of course difficult to interpret the accuracy or relevance of different estimated ratios. Research in order to “explain” or find transformations between different definitions of ratios and/or statistical methods used is very important. The same calculations and controls can be made for risk and consequence ratios.

I.4. INTERNATIONAL COMPARISONS

At the moment great efforts are being made to collate statistics from different countries in order to compare the safety situation. The exposure data is limited to inhabitants, vehicle fleet and vehicle mileage for the countries. Knowledge about the safety situation in different countries is increasing as a result of this work, but very limited results can be transferred from one country to another.

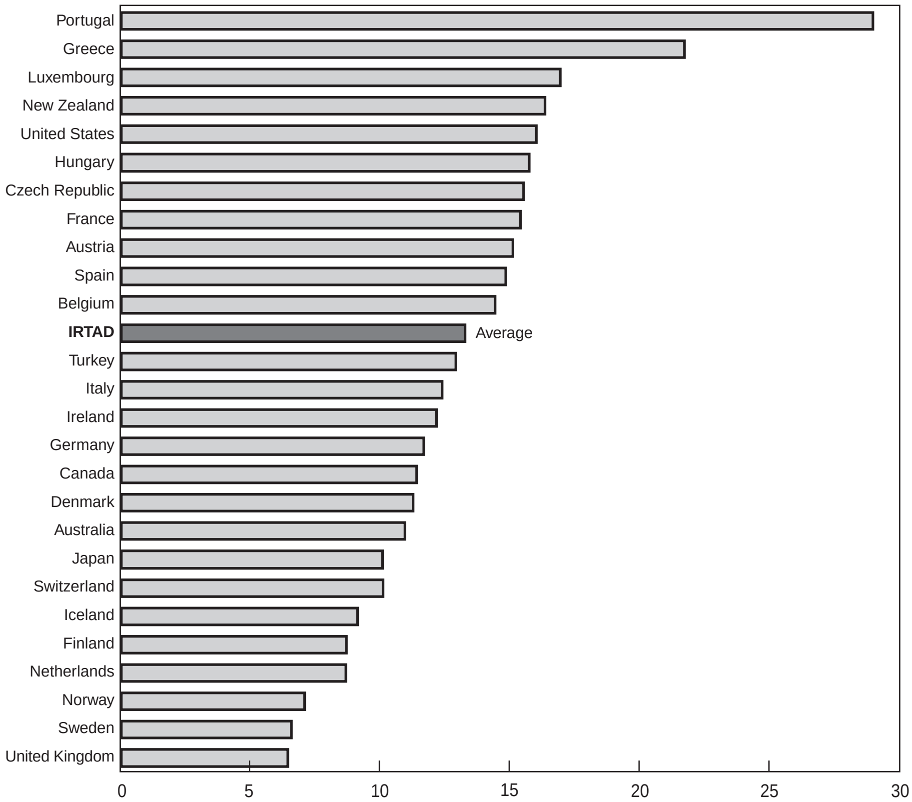
The OECD has as part of its Road Transport Research Programme an International Road and Traffic Accident Database (IRTAD) with annual aggregated accident information since 1970 which presently covers 27 countries. The data base is administrated by BASt in Germany. Figure I.5 presents a country comparison of fatalities per 100 000 inhabitants in 1995.

As illustrated by Figure I.5 the health fatality risk due to road traffic varies a lot between the presented countries.

For some countries road user person kilometres for drivers and passengers in passenger cars have been estimated. The fatality rates - number of fatalities per million person kilometres - are presented for the time period of 1990-1993 for passenger car drivers and passengers in Figure I.6.

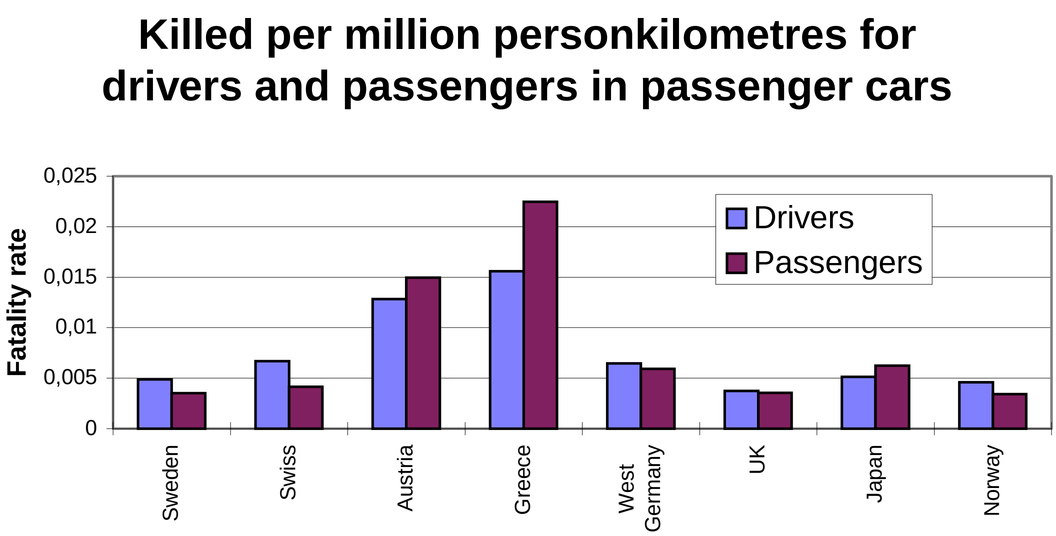
Further information is needed for a learning process. Three simple indicators are the use of seat belts among drivers and passengers, the proportion of intoxicated drivers and the speed distribution composition in different countries.

Figure I.5. **Country comparison of fatalities per 100,000 population in 1995**



Source: IRTAD.

Figure I.6. **Fatality rates for passenger car drivers and passengers in some countries 1990-1993**



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CHAPTER II PREDICTIVE MODELS FOR AGGREGATED DATA (ANALYTICAL MACRO MODELS)

Statistical modelling is a key source of knowledge within many scientific disciplines, especially those in which controlled experiments are difficult or expensive to conduct. The aim of this Chapter is to show why this approach is particularly useful within accident analysis, to demonstrate how it can be applied in practice, and to provide some general advice for potential users and practitioners. A number of methodologies which are designed to help understand and predict the accident process are reviewed and discussed, with a view to identify and evaluate potential accident countermeasures.

II.1. GENERAL FACTORS INFLUENCING AGGREGATE ACCIDENT DATA

Road accidents occur as a result of a potentially very large number of (causal) factors exerting their influence at the same location and time. It might be useful to distinguish between six broad categories of factors influencing accident counts.

First, accident numbers depend on a number of truly *autonomous factors, determined outside the (national) social system*, such as the weather, the natural endowment, the state of technology, the oil price, the population size and structure, – in short, factors that can hardly be influenced (except perhaps in the very long term) by any (single) government, no matter how strong the political commitment.

Second, they depend on a number of *general socio-economic conditions,* some of which are subject to political intervention, although rarely with the explicit purpose of promoting road safety, nor, more generally, as an intended part of transportation policy (for example, industrial development, (un)employment, disposable income, consumption, taxation, inflation, and public education).

At a third level, the size and structure of the *transportation sector,* and the policies directed towards it, clearly have a bearing on accident counts, although not usually intended as an element of road safety policy (for example, transport infrastructure, public transportation level-of-service and fares, overall travel demand, modal choice, fuel and vehicle tax rates, size and structure of vehicle park, driver license penetration rates). Most importantly, many of these factors are strongly associated with aggregate *exposure*.

Fourth, the accident statistics depend on the system of *data collection*. As discussed in Chapter I, accident underreporting is the rule rather than the exception and changes in the reporting routines are liable to produce fictitious changes in the accident counts.

Fifth, accidents counts, much like the throws of a die, are strongly influenced by sheer *randomness*, producing virtually inexplicable variation. This source of variation is particularly prominent in small accident counts. For larger accident counts, the law of large numbers prevails, producing an astonishing degree of long-run stability, again in striking analogy with the dice game.

Finally, accident counts can be influenced by *accident countermeasures*, that is measures intended to reduce the risk of being involved or injured in a road accident.

Although this last source of influence is generally at the centre of attention among policy-makers and practitioners in the field of accident prevention, it is far from being the only one, and may not even be the most important. To effectively combat road casualties at the societal level, it appears necessary to broaden the perspective on accident prevention, so as to – at the very least – incorporate *exposure* as a target for policy analysis and intervention. Accidents numbers are proportional, not only to the risk level, but also to the amount of exposure, as is illustrated by Figure I.1 of Chapter I.

II.2. PREDICTIVE MODELS VERSUS EFFECTIVENESS EVALUATIONS

To be able to attribute a change in the accident count to a particular countermeasure taken, the influence of the first five sources of variation described in II.1 must be established. This is no trivial task. Generally, two basic techniques are used to estimate countermeasure effectiveness: (i) predictive models and (ii) effectiveness evaluations (often referred to as before/after studies). Both techniques have their place in safety evaluation, each with its own strengths and weaknesses.

Predictive models, described in detail later in this Chapter, attempt to relate the independent variables of interest to accidents using a mathematical equation. In this way the user can examine how a change in a (set of) variable(s) affects the predicted number of accidents. Predictive models can be effective in situations where there are a large number of factors involved and/or when there are contaminating factors that cannot be controlled for through the experimental design. Because accidents are rare events, predictive models may also be useful in cases where the number of accidents at an individual site (or set of sites) is too small to evaluate in any reasonable period of time using an effectiveness evaluation.

Effectiveness evaluations can also play a valuable role. These studies treat the evaluation as if it were an experiment. That is, the safety of a certain set of roadways is studied both before and after a safety "treatment". Critical to the success of effectiveness evaluation is a proper experimental design that considers among other things the necessary sample size and attempts to eliminate or control for confounding factors. If the study is properly designed and appropriate analysis techniques are used, many safety researchers believe that this method provides a more direct and potentially cleaner approach than predictive equations. For example, Hauer (1991) states that "although the threats to the validity of conclusions drawn from before/after studies are many, they seem to be better known and easier to avoid than threats to the validity of conclusions drawn from cross-section comparisons". However, the before/after approach only provides an estimate of the effectiveness under the conditions studied, it does not provide a model with a theoretical basis and predictive capabilities. The literature on the subject is anything but conclusive with strong-held beliefs in the validity of both predictive models and effectiveness evaluations. For a given situation the researcher must consider the treatment(s) of interest, the potential for confounding variables, and the available data, in determining which technique to use. For more guidance on these issues the user should consult the *Accident Research Manual* (Council 1980) and the *Engineers' Guide to Program and Product Evaluation* (Griffin 1990).

Although rarely done, the strongest approach may be the development of predictive models which are then partially validated using effectiveness evaluations. Conducting before-after studies – which confirm key relationships represented by the predictive models – increases the confidence of the user in the validity of the predictive model without being limited by the narrow focus of a typical before/after study. Since the primary focus of this report is on safety theories and models, the remainder of this Chapter is focused on the development and use of predictive models. However, an overview of the techniques used to conduct effectiveness evaluations with accident data is provided in Appendix A.

II.3. ECONOMETRIC MODELLING – WELL SUITED FOR ACCIDENT ANALYSIS

Modern econometric modelling techniques can be very effective in sorting out the influences of the six sources of variation outlined in Section II.1.

The essence of econometrics is the blending of subject-matter theory, mathematical statistics, and empirical data. The theoretical foundation is essential. Econometrics is *not* a technique designed to explore what kind of empirical relationships (correlations) might possibly exist between an arbitrary set of variables. Rather, the essence of econometrics is to estimate the parameters of a *given* theory. *This theory must come from somewhere else than the data at hand themselves,* or the whole analysis will be more or less invalidated due to circularity of argument.

This is where econometrics, as an approach to empirical analysis, differs from mathematical statistics in general. Econometrics is deeply concerned with subject-matter theory as a prime prerequisite and basis for meaningful data analysis.

A most important point to note, however, is that this subject-matter theory *need not have an economic content*, in order for the principles and methods of econometric modelling to be applicable. It could be, e g, physical, biological, sociological, or simply any kind of common-sense, intuitive line of reasoning not depending on the data to be analysed.

There are several reasons why econometric methods would be at least as well suited for accident analysis as they are for economics.

Accidents are – with few exceptions – unwanted events, frequently even very traumatising ones. To a large extent, this precludes the use of perfectly controlled experiments to gain insights into the causal relationships governing the accident generating process.

Accident data are, therefore, although abundant, as a rule eminently non-experimental. Errors due to confounding effects can be avoided only to the extent that the relevant explanatory factors are included in the model, as is common practice in econometric modelling.

Accidents appear to be random in a more fundamental sense than almost any other social phenomenon (see Section II.4 below). An explicitly probabilistic approach is therefore not only, as in the case of economics, a convenient device to allow for the analyst's imperfect insight – it is a highly realistic picture of the accident process itself. Where the randomness introduced into economic models is subjective, simply reflecting a lack of knowledge, the randomness of the accident process is to a very large extent an objective feature of reality, reflecting the logical impossibility of casualty prediction at the micro level.

The analyst working with econometric accident models will, therefore, be in the very privileged position, compared to most econometric practitioners, of having excellent a priori knowledge of the shape of his disturbance distribution. Provided he has been able to identify all sources of systematic variation, his disturbance terms should follow the Poisson law. If not, the *overdispersion parameter* calculable from his data set would warn him that one or more independent variables have been omitted (see Section II.4 below). Unlike almost any other econometric application, the accident model is able to tell the analyst just how far he is from explaining all the systematic variation there is to explain.[1]

In examining accident data using econometric modelling techniques, it is in principle, not only possible to pinpoint the effect of certain accident countermeasures, but also the contribution made by those factors which are *not* usually thought of as elements in the accident causation process.

II.4. SYSTEMATIC VERSUS RANDOM VARIATION

Although accidents are the result of human choices and behaviour, they are not chosen (except for suicidal ones). On the contrary, when an accident happens, it is because certain road users (the accident victims) did not succeed in avoiding it, although they certainly did want to. Accidents are the unintentional side effects of certain actions taken for other reasons than that of causing injury or damage. They are random and unpredictable in the striking sense that had they been anticipated, they would most probably not have happened. Each single accident is, in a sense, unpredictable by definition.

It is probably fair to say that, nowhere within the realm of behavioural science, is there a set of phenomena coming closer than road accidents to being objectively random in character. No matter how much we learn about accident generating mechanisms or countermeasures, we would never be able to predict exactly where, when, and by whom the single accident is going to occur. Accidents are random in a much more fundamental sense than almost any other event occurring in society.

This suggests that any analysis of the accident generating process should be based on an explicitly probabilistic model, according to which single events may occur at random intervals, however with an almost constant overall frequency in the long term. Although the single event is impossible to predict, the accumulation of such events may very well behave in a perfectly predictable way, which can be described by means of precise mathematical-statistical relationships.

The fact that accidents are random and unpredictable at the micro level, does not mean that their number is not subject to causal explanation or policy intervention. Through the design of road systems and vehicles and through the choice of behaviour of road users, the *probability* of an accident occurring can be influenced, thereby altering the long-term accident frequency (just as the odds of a game can be changed by loading the die).

This long-term accident frequency – the *expected number of accidents* per unit of time – could be considered the result of a causal process. This process accounts for the striking stability observable in aggregate accident data, in which the random factors (“noise”, “disturbance”) which have a decisive effect

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[1] To this purpose, certain specialized goodness-of-fit measures have been developed (Fridstrøm et al 1995). These measures are even able to warn the analyst when his model is *overfitted*, leaving even less (unexplained) variation for the residuals than the amount appropriate for a perfectly specified Poisson model.

at the micro level, are "evened out" by virtue of the law of large numbers. The causal process determines the expected number of accidents, as a function of all the factors making up the causal set (the causes).

To be specific, let $\lambda(r,t)$ denote the expected number of accidents occurring during period t at location[2] r. The expected number of accidents is, of course, not a constant, it varies with location and time (i.e. with r and t). This variation, attributable to the various causal factors, is *systematic*. Unlike the random or pure chance variation, the systematic variation can – in principle – be influenced and controlled. Only the systematic variation is of interest from a policy point of view.

Let $\mathbf{x}(r,t) = [x_1(r,t), x_2(r,t), \ldots, x_n(r,t)]$ denote the set of causal factors determining $\lambda(r,t)$, i.e.

$$\lambda(r,t) = E[y(r,t) | \mathbf{x}(r,t)] = f\{\mathbf{x}(r,t)\}, \qquad \text{(Eq. 1)}$$

where y(r,t) denotes the observed (factual) number of accidents at time t in location r.

With this notation (suppressing the indices r and t), the total variation in accident numbers can be split into random and systematic components as follows (Miaou 1995):

$$\text{var}(y) = E[\text{var}(y|\mathbf{x})] + \text{var}[E(y|\mathbf{x})]. \qquad \text{(Eq. 2)}$$

Here, the first term corresponds to the random variation (normal spread in y, given the systematic factors x), and the second term to the systematic variation (spread between the respective, expected numbers of accidents $\lambda(r,t)$)[3].

To understand the process producing accident numbers y(r,t), one must (i) acquire information or make an assumption concerning the general *functional form f*, (ii) determine the set of *explanatory (independent) factors* **x**, and (iii) estimate the *parameters* entering the function $f(\mathbf{x})$. In so doing, it usually helps (iv) to have a good notion of the nature of the *probability distribution* governing the random variation $y(r,t) - \lambda(r,t)$, since the relative efficiency of alternative estimation techniques is likely to depend crucially on the distributional characteristics of this random "disturbance" term.

II.4.1. Functional form

The most commonly used functional form in multivariate analysis is the linear regression model

$$\lambda_i = \sum_j \beta_j x_{ji} \ , \qquad \text{(Eq. 3)}$$

where, for simplicity, index i now replaces r *and* t. Note that the x's could be of virtually any form, i.e. the model is linear *in the parameters β*, but not necessarily in the explanatory factors x.

We know that the expected number of accidents is necessarily a non-negative number. In many applications (especially when working with small accident counts), it might be a good idea to build this

[2] For example, a road stretch, an intersection, an area, or even an entire country. By the same token, the time period considered might be of any length.

[3] **x** and y are (vector) variables generated by a stable, simultaneous multivariate random process. The moments of the conditional expectation and variance of y can be calculated by integrating over the range of **x**.

information explicitly into the model, by specifying a functional form *f* which cannot take on negative values, for example,

$$\lambda_i = e^{\sum_j \beta_j x_{ji}}, \qquad \text{(Eq. 4)}$$

meaning that the *log* of the expected number of accidents is a linear function of a parameter vector $(\beta_1, \beta_2, \ldots)$. In this (log-linear regression) model, the relationship between the independent and dependent variables is essentially multiplicative in character, an intuitively appealing property in most accident modelling applications.

II.4.2. Choice of regressors

Little can be said in general about the relative merits of potential explanatory variables. In most cases, however, it is paramount to include some measure of exposure, as this is likely to be the single most important determinant of any accident toll.

It is sound analytical practice, however, to base the choice of explanatory variables on something other than curve-fitting or multiple correlation structures. Ideally, the choice of variables follows almost directly from the question to be answered, in combination with the theory to be relied on. In practice, however, a certain amount of empirical trial and error is usually involved in the model specification search process. One should be aware, however, that in the course of such a "data mining" process, one gradually loses control of the statistical significance level and risks ending up with a model which, although it fits the data nicely, can hardly be generalised outside the sample upon which its parameter estimates have been based.

In general, the interpretation of any parameter β_j is the *partial effect* of x_j on the expected number of accidents, *given all the other factors included in the regression.* The estimate of β_j is statistically unbiased (or at least consistent) only if there are *no relevant explanatory variables omitted* from the model, which happen to be *correlated with the variable of interest* x_j.

II.4.3. Estimation

Parameters can be estimated in a variety of ways, the two most common main principles being (generalised) *least squares* and (quasi-)*maximum likelihood.* Maximum likelihood estimation is generally the (most) efficient method in large samples, given the distributional assumptions. In smaller samples, its efficiency is largely unknown. Least squares methods have the advantage of being applicable even if the probability distribution is not fully specified, although their efficiency does vary with the true, underlying probability distribution. In certain cases (such as normally distributed disturbance terms), the maximum likelihood and least squares estimation methods coincide.

II.4.4. Probability distribution

Rather compelling arguments[4] can be found in support of the assertion that accident counts must follow the *Poisson* probability law, given by the formula

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[4] If, in general, (i) the probability that a certain type of event (for example, a road accident) occurs in area r within a certain, short time interval is constant throughout a certain period t, and (ii) if the probability of an event does not

$$P[y(r,t) = m] = \frac{[\lambda(r,t)]^{m} \cdot e^{-\lambda(r,t)}}{m!} \qquad \text{(Eq. 5)}$$

As before, $\lambda(r,t)$ denotes the expected number of events during period t in area r, while y(r,t) is the corresponding, actual number of events.

In terms of analysis, the Poisson assumption has a number of useful and interesting implications (Fridstrøm et al 1995). Most importantly, the variance of a Poisson variable equals its expected value, both being equal to the Poisson parameter – $\lambda(r,t)$. That is, having estimated the expected value, one also knows, in a sense, how much random variation is to be expected *around* that expected value.

Even if complete and correct knowledge of all the factors x_j causing systematic variation, and of all their coefficients β_j can be acquired, so that the expected number of accidents $\lambda(r,t)$ (that is, *all there is to know* about the accident generating process) *is known*, the accident number cannot be predicted with certainty: There would still be an unavoidable amount of purely random variation left, the variance of which would be given – precisely – by $\lambda(r,t)$. The residual variation should never be smaller than this as this would indicate that part of the purely random variation has been misinterpreted as systematic, and erroneously attributed to one or more causal factors.

In practice all risk factors are rarely all correctly identified and their coefficients impeccably estimated, so that the expected number of accidents is virtually known. A somewhat more realistic probability model arises if it is assumed that the Poisson parameter $\lambda(r,t)$ is itself random, and drawn from a gamma distribution with shape parameter ξ, in which case the observed number of accidents can be shown (Gourieroux et al. 1984 a, b) to follow a *negative binomial* distribution with expected value $E[\lambda(r,t)] = \mu(r,t)$ (say) and variance

$$\sigma^2(r,t) = \mu(r,t)\,[1 + \theta\,\mu(r,t)], \qquad \text{(Eq. 6)}$$

where $\theta = 1/\xi$.

In the special case $\theta=0$, the gamma distribution is degenerate and we are back to the simple Poisson distribution, in which the variance equals the mean. θ is the "*overdispersion parameter*", and models in which $\theta>0$ are "overdispersed". In such a model, the amount of unexplained variation is larger than the normal amount of random disturbance in a perfectly specified Poisson model, meaning, that not all the noise is purely random. That is, the model does not explain all the systematic variation, but lumps part of it together with the random disturbance term.

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depend on any previous events, then it can be shown mathematically that the probability of m events occurring in period t is given by the Poisson formula (Griffin, 1989).

The assumptions (i) and (ii), underlying this derivation, are much less restrictive than they may seem. This is so on account of the convenient invariance-under-summation property of the Poisson distribution: any sum of independent Poisson variates is itself Poisson distributed, with parameter equal to the sum of the underlying, individual parameters. Thus all we need to assume is that, through some very short time interval (say, a minute, second, or fraction thereof), the accident probability can be considered constant, and that events occurring during disjoint time intervals are probabilistically independent. In such a case the number of events occurring in a given region r during a given period t (week, month, or year) will indeed, be Poisson distributed.

The overdispersion parameter can be used to test whether or not the independent variables explain all the explicable (systematic) variation, (that is, if there is residual variation left in the model over and above the amount that *should* be there in a perfectly specified and estimated Poisson model). However, even if the overdispersion is found to be zero, it does not follow that the analyst has found all the true causal factors and correctly calculated their effects. The generalised Poisson formulation is no guarantee against spurious correlation being interpreted as causal, only against *too much* correlation being interpreted that way. In principle, two quite distinct sets of alleged causal factors could provide equally good and apparently complete explanations, as judged by the overdispersion criterion.

As in other econometric work, therefore, the choice of independent variables must be guided by theory and professional judgement, rather than by curve-fitting. This is elaborated on in the next two sections.

In Appendix B an illustrative example is given of a spatial Poisson analysis. The example is taken from Japan and intends to compare results of some of the models introduced in this section.

II.5. THE HYPOTHETICAL EXPERIMENT – A KEY CONCEPT OF NON-EXPERIMENTAL RESEARCH

Econometric modelling can be viewed as a scientific substitute for the perfectly controlled experiment, applicable in all cases where it is impossible to vary one independent variable at a time, while keeping all other influences constant. The great bulk of accident research falls into this category.

In an econometric model, rather than fixing the values of the independent variables through a controlled experimental design, the set of data that nature or society itself has produced has to suffice. By building a *model* mimicking the process that generated the data, and estimating its *parameters* in such a way as to reproduce the observations to the largest possible extent, it is in principle possible to separate out and assess the impact of each independent variable. In essence, by linking the variation in the dependent variable to the joint variation of the independent variables, certain partial patterns of covariation emerge and are condensed in the form of model parameter estimates.

To set up a reliable econometric model of accidents, considerable caution and professional judgement is, however, called for. First and foremost, *the analyst must have a clear idea of what question(s) he wants to answer,* and specify the model accordingly. The aim is usually *not* to obtain a maximal goodness-of-fit. Nor is the goodness-of-fit statistic necessarily of any particular interest as a measure of model performance.

Working with non-experimental data does not mean that the concept of an experiment can be done without, – on the contrary. In most cases, models are built in order to *measure partial effects* defined in terms of a *hypothetical experiment* in which a given "treatment" (countermeasure) is applied, and the resulting change in accident toll or frequency can be "read off". For policy purposes, it is usually some kind of *conditional prediction* that is of interest. By drawing on the partial effects estimated, the difference between, on the one hand, a *reference* ("business-as-usual") scenario and, on the other hand, an *intervention* scenario, can be assessed. In the latter scenario, certain policy (or policy sensitive) variables entering the model are assumed to develop differently compared to the reference path. As a decision support tool such models may become quite valuable, ideally telling us – for instance – what accident rate reductions can be expected from certain types of traffic safety measures, (certain) other things being equal.

II.6. TOO MANY OR TOO FEW VARIABLES

Whenever a policy intervention is carried into effect, some factors are going to change, as a result of the measure taken. In general, *any variable whose value is not supposed to be held constant during the hypothetical experiment should not be included among the regressors*.

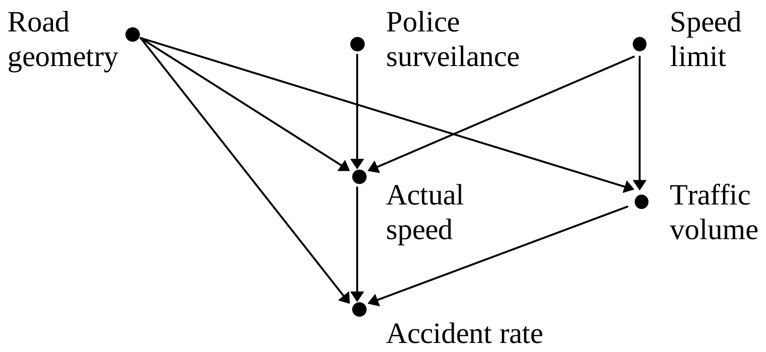
For instance, when a road is widened and/or improved, the average speed may go up and the traffic volume may increase, at least on that particular road link. If, however, speed has been included among the regressors of the model, this amounts to asking for partial effects given constant speed. But this may not be the question we want to ask, and the model will provide unrealistic predictions as compared to a real world situation.

To recognise the relevance of this argument, imagine instead that the accident countermeasure considered is a lowered speed limit. Most professionals and practitioners will immediately realise that in this case, it does not make sense to control for actual speed.

In general, there is reason to warn against the use of any “independent” variable whose value is subject to choice by the decision makers under study (usually, the road users), for the simple reason that such variables are not, in effect, independent (or exogenous, in the terminology of econometrics). One might refer to this source of error as *endogeneity bias* (endogeneity being the opposite of exogeneity).

This principle is illustrated by Figure II.1, in which the arrows represent the direction of assumed causal influences. Three variables are exogenous, that is, determined from outside the road user population: road geometry, police surveillance, and speed limits. Two variables are intermediate: actual speed and traffic volume; these are not independent, but determined by road user decisions in conjunction with the exogenous factors. The last (dependent) variable – the number of accidents – depends on all the exogenous and intermediate factors, directly and/or indirectly.

Figure II.1. **Causal path diagram for accidents on a given road stretch**



Source: Fridstrøm (1992)

To estimate the effect of, for example, speed limits (or road geometry) on accidents, the analyst is advised either (i) to estimate one equation for each endogenous variable (that is, one for each variable with an ingoing arrow from any of the other variables), or, if that is not possible, (ii) to estimate one "reduced form" equation explaining the final dependent variable as a function of truly exogenous variables only[5]. In the latter case, only the sum of all direct and indirect effects will be identifiable.

Endogeneity bias occurs when the analyst has included variables that, given the hypothetical experiment envisioned, do not belong there. The opposite error is equally common, and consists in including too few variables. Omitted variable bias occurs whenever a regressor is correlated with some relevant explanatory variable not included in the model. In such a case, the effect due to the excluded variable may be ascribed to the included one, inflating (or deflating) the coefficient of the latter. This situation can also be illustrated by Figure II.1. If speed limits are correlated with the measures of road geometry (as they would normally be, in a sample consisting of various road sections), the omission of road geometry measures from the equation would probably lead to biased estimates of the partial effect of speed limits. Since higher speeds are usually allowed on better (and safer) roads, the chances are that an equation omitting road geometry would predict a decreasing accident toll as speed limits increase.

Whether or not – vice versa – speed limits should be included in an equation to estimate the effect of road geometry, depends on the precise nature of the hypothetical experiment. If the idea is to keep speed limits down (i e, constant) even though the roads are improved, so as to be able to measure the effect of road geometry per se, it would be correct to include speed limits in the equation. If, on the other hand, the (more realistic?) situation is studied, in which speed limits are adjusted so as to reflect the quality of the road, the estimate would be subject to endogeneity bias if speed limits were included in the equation.

This example serves to illustrate the importance of thinking through the hypothetical experiment prior to specifying the model. The "correct" model depends not only on the true causal process having generated our data, but also -- crucially -- on the precise question to be answered.

Unfortunately, it will not in general be known whether the condition of zero correlation between included and omitted variables is fulfilled[6]. More often than not, variables are omitted precisely because they are unknown, or at least not measurable for those units of observation which make up the sample. The best the analyst can do in such cases is to apply professional insight and judgement in order to assess the probability, sign and likely strength of a correlation between omitted and included variables, and qualify the results accordingly.

On the other hand, if the (usually unknown) correlation between omitted and included variables is zero, omitting the variables does not bias the parameters of the independent variables retained. In other

[5] More precisely, one should solve the system of equations for those variables whose equations *are* estimable, and estimate those equations. If, for example, the traffic volume is observable but not the actual speed, two equations should be estimated: One explaining the traffic volume as a function of road geometry and speed limits (and possibly other variables, not shown in the diagram), and one explaining accidents as a function of traffic volume, road geometry, police surveillance and speed limits. The latter is a «reduced form» equation in the sense of not containing actual speed, but only its exogenous determinants.

[6] This is so because, *by definition,* the least squares principle of estimation amounts to fixing the parameter values in such a way as to make the residuals (which inlude all omitted variables) orthogonal to (uncorrelated with) every independent variable included.

words, omitted variables are only a problem when their sum is correlated with (any of) those variables whose partial effect we do want to estimate[7].

In most accident models, exposure plays a key role among explanatory factors. Although, in keeping with the above, it is conceivable that unbiased countermeasure effect parameters can be derived even if exposure is omitted, such a procedure is advisable only in situations where exposure is almost constant throughout the sample. In any other situation, variation in exposure will account for such a large part of the variation in casualties, that the disturbance variance is likely to overshadow any systematic variation found, if exposure is lumped together with the former rather than the latter. In other words, even if the effect parameter estimates were still unbiased, they would be very imprecise (have high standard errors). In most cases, moreover, exposure will not be uncorrelated with all the other regressors of interest.

It is entirely possible that controlling exposure is not part of the hypothetical experiment of interest. For instance, when assessing the accident impact of (new) bicycle paths, the increased bicyclist exposure (caused by more people using the bicycle, not only on the relatively safe bicycle paths themselves, but also area-wide on the entire road network) should not be controlled away.

In such a case a multiplicative decomposition approach[8] is, ideally, called for, in which a separate relation explaining exposure is also estimated. In general, whenever a variable belongs in the equation on account of its major influence on accident numbers, but should be omitted on account of the hypothetical experiment considered, a multiple equation approach is needed in order to keep track of all interesting effects.

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[7] A frequently cited objection against econometric models or multiple regression analysis is that omitted variable bias represents an uncontrollable source of error, since one never really knows what is contained in the disturbance term. Against this viewpoint, it might be argued that omitted variable bias (confounding factors) is a powerful source of error in *any* empirical study (except those based on perfectly randomized experiments), but *less so* the more variables are taken into account (that is, the fewer variables are *not* omitted). Simple, bivariate frequency table or correlation analyses are, in this respect, vastly more error-prone than multiple regression models etc. This fact is, however, not entirely self-evident, since traditional bivariate analyses, unlike econometric models, usually do not contain an explicitly formulated "error" or "disturbance" term. While the econometric analyst is invited (or forced), in the course of his model specification process, to pay attention to his error term and its content, this is unfortunately not the case for the user of simpler, bivariate methods of inference.

[8] In a single equation ("direct") casualty or accident model, the number of accidents or accident victims (or a particular subset thereof) is explained directly as a function of the independent variables, in a single stage. In a component model, on the other hand, the number of victims or accidents is decomposed multiplicatively, forming a multi-stage chain of relations, for instance like this:

$$\underbrace{fatalities = \frac{fatalities}{injury\ accidents}}_{s\,=\,severity} \times \underbrace{\frac{injury\ accidents}{traffic\ volume}}_{r\,=\,accident\ risk} \times \underbrace{traffic\ volume}_{e\,=\,exposure}$$

The number of road fatalities (*f*) (that is, the number of death victims) is decomposable into a severity measure (*s*), a risk measure (*r*), and an exposure measure (*e*). By definition, $f = s{\cdot}r{\cdot}e$. An indirect (component) accident model is one in which separate equations are used to explain (in this case) *s, r,* and *e*.

Surprising insights can be gained from the study of such simple decompositions, if only by plotting the time series of each component and their product along a time axis. Even more information is gained when each component is regressed on a set of relevant explanatory variables. This is the approach taken in the DRAG model for Quebec described in Appendix C.

II.7. MULTICOLLINEARITY – A MISUNDERSTOOD ISSUE

Another frequently discussed modelling issue is *multicollinearity*. Perfect multicollinearity occurs when one or more explanatory variables can be expressed as an exact, linear function of the other ones. In such a case, it is impossible to separate the influence of that particular variable from that of the others. Its parameter is unidentifiable and hence inestimable.

Less than perfect multicollinearity occurs when the relationship is not exact, only approximate. In such a case, one (or more) variables turn out to be highly correlated with a certain linear combination of other regressors.

It is not uncommon to see lengthy discussions of the "multicollinearity problem", or assertions to the effect that regressors "should not be collinear". This issue is largely misunderstood. Multicollinearity is an inescapable aspect of non-experimental data, and there is not much one can do about it, except setting up a controlled experiment, that is, discarding non-experimental data altogether.

Econometric methods have been designed precisely in order to make use of non-experimental (that is, multicollinear) data, and – except for cases in which the multicollinearity is "perfect", yielding a singular (unsolvable) system of equations – such collinearity only means that certain parameters will be estimated with regrettably low precision. This occurs, for example, when two or more independent variables move up and down more or less together, throughout the sample. Since, however, any decent statistical software package provides, not only the parameter estimates, but also their standard errors, the analyst is appropriately warned against this lack of precision.

It is widespread practice in cases like this to remove one or more variables from the equation. While this may apparently "solve" the problem of imprecision, in principle, a different hypothetical experiment than the one corresponding to the original equation is defined, *all parameters of the equation acquiring a new interpretation*. Put simply, the same partial effects are no longer being estimated.

The choice of variables should be made, not on the basis of their mutual empirical covariation, but on the basis of the theory, professional insight and the hypothetical experiment to be conducted.

It should be noted that it is seldom a good idea to include two variables measuring more or less the same phenomenon. In such a case their effects would more or less cancel each other out, both parameters coming out as largely insignificant, although possibly providing a nice contribution to the fit.

In many cases, a *multiplicative decomposition* may prove useful, even for certain *independent* variables. Rather than including the two highly collinear variables "private car mileage" and "heavy vehicle mileage" for example, "(log of) total mileage" and "(log of) heavy vehicle share of total mileage" might be used. In a Poisson or log-linear regression model, the coefficient of the former will then interpret the overall accident elasticity with respect to exposure, while the coefficient of the latter will express the separate effect of increased heavy vehicle traffic.

II.8. FORMULATING AN ACCIDENT MODEL

II.8.1. Cross-sectional versus time-series modelling

Accident models could be based on cross-sectional (spatial) or time-series (temporal) variation, or both. Both approaches have their pros and cons.

Cross-sectional models

Cross-sectional accident models exploit the variation between different entities observed at the same time, linking the differing casualty counts to the varying characteristics of the entities. Here, an "entity" could be any kind of geographically defined unit, or, indeed, any sort of identifiable physical or institutional object, such as a person, a family, a company, a vehicle, a car make, or a *group* of such micro units exhibiting certain common characteristics.

Cross-sectional data sets typically exhibit lots of variation, however often without strong covariation (collinearity) between the independent variables of interest. Also, cross-sectional data sets can often become quite large. Both of these features serve to facilitate the derivation of precise parameter estimates (see Section II.4).

The assumption implicit in cross-sectional analysis is that the units of observations are not different in any other essential way than what is captured by the variables entering the model. Cross-sectional units of observations are, however, often very different in character, sometimes in ways not easily discernible by the analyst and hence difficult to control for.

It is an open question whether parameters derived through cross-sectional analysis can be applied for the purpose of prediction and forecasts. Models based on cross-sectional or time-series data sets, respectively, often come up with very different estimates on the same parameter. In part, this is explicable in terms of different time horizons: while time-series models typically provide estimates of short term effects, the cross-sectional model parameters usually have a long term effect interpretation. But in many cases the differences in outcome between the two approaches appear too large to be accounted for in this way. It is not in general obvious which of the two approaches provide the "correct" answer, if any.

Time series models

Time-series models essentially involve repeated observations of the same physical or institutional object. The unit of observation is a point or period in time (hour, day, month, year, ...)

In time-series modelling, heterogeneity between the units of observation is much less of a problem. On the contrary, there may often be too little variation, especially as time series data sets tend to show considerable collinearity between potential regressors. Also, time series models usually exhibit more or less pronounced autocorrelation, that is, correlation between successive disturbance terms, originating from the fact that all the relevant variables have not been included in the set of regressors.

A variety of specialised techniques have, however, been developed, in order to deal with autocorrelation, autoregression (that is, the dependent variable depending on previous realisations of itself), or other aspects unique to time series analysis. Indeed, it might be argued that the existence of highly specialised time series analytical techniques is a prime advantage of the time series modelling approach as compared to cross-sectional studies, turning the “nuisance” of autocorrelation etc. into an asset in the form of additional information to be exploited[9].

Combined cross-section/time-series models (panel data models)

Panel data models exploit combined cross-section/time-series data sets -- that is, repeated observations on a given cross-section of units.

For panel data, certain specialised techniques are also available (see, e g, Hsiao 1986). Alternatively, one may choose to handle such data as just another, large cross-sectional data set. By suitably organising the data set, one might also be able to exploit the information inherent in the longitudinal autocorrelation, if any, as in a pure time series data set. Needless to say, panel data constitute the richest source of information obtainable.

II.8.2. Linear models

A linear model is one in which the systematic (non-random) part is expressed as a linear function *of the parameters*:

$$y_i = \sum_{j=1}^{J} \beta_j x_{ji} + u_i \qquad \text{(Eq. 7)}$$

where y_i is the dependent variable, x_{ji} are the independent variables, and u_i is the random error term. Note that the model is *not* necessarily linear *in the variables*: the x_{ji} could consist of virtually any (known) transformation of any set of independent variables of interest (logarithmic, quadratic, cubic, or trigonometric functions). Linear models can be estimated consistently by means of ordinary or generalised least squares estimation techniques.

A white noise model is one in which all the disturbance terms are independent and identically distributed, implying constant error variance (homoskedasticity) and zero autocorrelation. Only in this case is the ordinary least squares procedure in some sense optimal (efficient).

A model is autocorrelated if there is a non-zero *covariance* between the error terms pertaining to different time points ($\text{cov}(u_s,u_t) \neq 0$). It is heteroskedastic if the error *variance* is not constant across the sample ($\text{var}(u_s) \neq \text{var}(u_t)$).

Autoregression means that the dependent variable is a function of previous (lagged) representations of itself:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + x_t + u_t\,. \qquad \text{(Eq. 8)}$$

[9] Autocorrelation may be present in cross-sectional data sets as well, depending on how the data have been sorted. Techniques to exploit the information inherent in spatial autocorrelation structures are, however, as of yet only in an early stage of development (Blum et al 1990, Gaudry et al 1994, Liem and Gaudry 1994), as this problem is much more difficult to deal with in a formalized mathematical way.

A first order autoregressive process exists if $\alpha_1 \neq 0$ and $\alpha_j = 0 \; \forall j > 1$. In general, the process y_t is pth order autoregressive if $\alpha_p \neq 0$ and $\alpha_j = 0 \; \forall j > p$. By recursion, even in a first order autoregressive process, y_t depends on all previous realisations y_{t-j} (j>0).

A variety of statistical techniques exist to deal with the different aspects of dynamic times series processes, such as seasonal and cyclical variation, trend patterns, etc. Among the more well-known approaches is the ARIMA (AutoRegressive Integrated Moving Average) model, largely originating from the work by Box and Jenkins (1976).

II.8.3. Generalised linear models

Generalised linear models (a term apparently coined by McCullagh and Nelder 1983) usually refer to a framework in which

$$h(\lambda_i) = \sum_j \beta_j x_{ji} \quad , \qquad \text{(Eq. 9)}$$

is specified, where h is commonly referred to as the *link function*. The expected value of the dependent variable is linked to a linear regression term by means of some general, monotonic function. The disturbance term (y_i - λ_i) could be consistent with any one of a large (so-called exponential) family of probability distributions.

It is not hard to see that the count data (i e, Poisson and negative binomial) models described above fit into this category. Examples of how this methodology can be applied to accident analysis are found in Appendix B, as well as in Maycock and Hall (1984), Miaou et al (1992), Fridstrøm et al (1995), Kulmala (1995), to mention a few.

In general, count data models do not exploit the information contained in possible autocorrelation structures. Certain attempts have, however, been made to integrate the advantages of count data modelling with those of time series modelling (Zeger 1988, Brännäs and Johansson 1992), and a methodology to handle panel data has been developed by Hausman et al. (1984).

The *DRAG model* for Quebec (Gaudry 1984, Gaudry et al 1995) constitutes a very ambitious attempt to explain the development of aggregate exposure, accidents and their severity over time. (See Appendix C). Beside the very large number of explanatory variable taken into account, the prime distinguishing feature of the DRAG model is its use of Box-Cox-transformations, given by:

$$x^{(\psi)} = \begin{cases} \dfrac{x^{\psi} - 1}{\psi} & \text{for } \psi \neq 0 \\ ln(x) & \text{for } \psi = 0 \end{cases} \qquad \text{(Eq. 10)}$$

to relax the linearity assumption usually embedded in a regression model. Being continuous and differentiable at ψ = 0, the Box-Cox function includes the cubic (ψ=3), quadratic (ψ=2), linear (ψ=1), square root (ψ=0.5), logarithmic (ψ=0), and reciprocal (ψ=-1) functional forms as special cases.

In general, the Box-Cox regression model takes the following form:

$$y_t^{(\omega)} = \sum_{j=1}^{J} \beta_j x_{tj}^{(\psi_j)} + u_t \, . \qquad \text{(Eq. 11)}$$

Ideally, all the parameters (ω, ψ_j and β_j, $j=1,2, ..., J$) are estimated simultaneously. Thus, the data are allowed to determine, not only the coefficients, but also the optimal functional form of certain relationships (within the Box-Cox family of monotonic functions).

Log-linear models are formulations in which the logarithm of the dependent variable is expressed as a linear function of the right-hand side coefficients and the error term:

$$\ln(y_t) = \sum_{j=1}^{J} \beta_j x_{tj} + u_t \qquad \text{(Eq. 12)}$$

It can be viewed as a special case of the Box-Cox regression model, in which one sets $\omega=0$ and lets all the ψ_j be pre-specified and (by assumption) known. Note that this model is different from the Poisson specification, in that the disturbance term becomes multiplicative (in relation to y_t) rather than additive.

II.8.4. Specifying the random disturbance structure

A (generalised) Poisson model is one in which the dependent variable is assumed to follow the Poisson distribution or a generalisation thereof. These models are often referred to as *count data* models, because the dependent variable is a non-negative integer, i. e. a count variable. If only for this reason, count data models are a natural choice in the analysis of accidents and victims. Moreover, there are strong reasons to think of accidents as the outcome of some underlying Poisson process.

However, it does not follow that (generalised) Poisson regression models are necessarily the best (or only) way to analyse accidents.

The (generalised) Poisson model is particularly well suited for data sets involving small accident counts. The fact that a large number of counts may be zero poses no problem within the Poisson modelling framework.

The limiting distribution of the Poisson is normal. For large accident counts, therefore, one might as well work with Gaussian models (i e, normally distributed disturbance terms). For such models, a well developed error theory and software exist, allowing the analyst to specify complicated random disturbance structures, involving (a) multiple-order autocorrelation and/or (b) heteroskedasticity functions. Moreover, in cases where it is not a priori obvious what would be the appropriate functional form of certain partial relationships, the use of (c) Box-Cox transformations represents a powerful analytical tool. The software developed for the DRAG model for Quebec (Gaudry et al 1993) offers the analyst all three of these features.

II.9. MODELS AS PICTURES OF REALITY

Road accidents can be viewed as causally determined, random events occurring as the outcome of a complicated, *multivariate probabilistic process*, containing systematic as well as stochastic variation.

This strongly suggests the use of *multivariate probabilistic (econometric) models* as a fruitful way of gaining insight into the process and how to influence it.

In fact, there are few – if any – cases within the behavioural sciences, where an explicit, multivariate probabilistic model can be relied upon to provide a more complete picture of reality than in the field of accident analysis. Not only are there, in most industrialised countries, an abundance of relevant data available, which can be exploited in order to establish policy-relevant, *systematic* relationships governing the accident counts. Even the *random* part of the accident probability process is to a large extent understood, making it possible to predict just how good a fit the "perfect" accident model should provide.

The accident analyst will, therefore, be able to tell whether his model is underfitted, overfitted, or just about suitably large in terms of explanatory variables. Accident data lend themselves to econometric modelling like few other phenomena within the realm of behavioural science.

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CHAPTER III RISK FACTOR MODELS - ANALYTICAL MODELS ON THE INDIVIDUAL (MICRO) LEVEL

III.1. DANGER AS A RESULT OF THE TRANSPORT SYSTEM COMPLEXITY

The topics that were covered in Chapter II looked at models based on aggregated data. This Chapter focuses on the individual level. The emphasis is on models which describe processes of individual behaviour in traffic or demonstrate interactions between the different elements of the traffic and transport system.

Such models are used to understand or predict driver and pedestrian actions – in different road and vehicle situations or specific manoeuvres. Driver or pedestrian behaviour can be analysed in relation to traffic risks. The risk factors that influence the frequency of road accidents can be identified and with this knowledge – by taking into account road users in dangerous road environments – it is possible to design cars, roads, legal and educational measures, and driver psychology programmes to enhance traffic safety.

When trying to improve traffic safety and investigate traffic accidents, the fundamental question to answer is: where do danger and damage come from? Basically, what causes damage, is the mechanical dissipation of energy during a collision, as identified by Haddon et al. (1964): First, there is the collision of the vehicle with another vehicle, an obstacle or a pedestrian on the road. This is followed by a second collision of the occupants against the internal structure of the vehicle, then by a third collision of the occupants' internal organs against their skeleton. It is this potentiality of collisions liable to cause damages which makes the road transport system dangerous. The seriousness of the damage results from a relation between the force of the impact and the shock resistance of the vehicles, as well as the resistance to shock of human tissues and organs during a collision.

Because of the evolution of the transport and traffic system – as described in Chapter II of the main report – the complexity of the system has increased as well as the danger due to technical failures or human errors. The individual has to deal with ever more complex situations. This leads to errors and increases the danger in specific situations. The fourth paradigm (see Section II.3.4 of the main report) indicates that these failures or errors have to be accepted and that the danger should be reduced by better risk management in the traffic and transport system.

Danger is present in the heart of the driver/vehicle/road system. It is a state of the system; but its measure – risk – is evaluated in a subjective way by those who use the system, and in a objective way by those who manage it. The road transport system and its components are more or less reliable but vulnerable. They can be in states or situations which modify the occurrence or seriousness of an accident. The danger remains in a latent state, but it will materialise if the vulnerability of the system increases.

In the road traffic system, the sources of danger are numerous and interactive, depending on the driver/vehicle/road components of the road transport system. Confronted with a dangerous situation, each component of the system will manage a disturbing event depending on its state. Vulnerability can be described as an "operator" which reflects the impact of this disturbing event and which can either lead to an accident or assures normal functioning according to the prevailing relationship of forces between disturbance and vulnerability.

Vulnerabilities are dealt with in rather structural terms by referring to fragility, direct and indirect dependence or ungovernability. On the one hand there are sources of danger, and on the other hand vulnerabilities, which can be seen as system deficiencies (in analogy with immune deficiencies). For instance, as speed is a source of danger, the marketing of cars with powerful engines increases the system's vulnerability. Density is also a factor of vulnerability. The more dense traffic is and the more data the driver has to manage, the greater are the chances that errors will be made. Should a disturbance occur, the number of vehicles involved in an accident will be even greater. Thus, the system contains components that interact, and factors which lead to risk.

Models are a good basis for analysing risk factors within the system and the subsystems. The risk models and the (dys)functioning of the relevant elements of the road transport system are useful for car manufacturers, road and traffic engineers and those who develop programmes for driver education and improvement. Thus, models focusing on the individual make it possible to develop concepts and research methods for traffic safety. The sections below show the different steps in achieving this target and describe various models at different levels and of different quality. However, it should be noted that as traffic safety sciences are relatively recent, much has still to be done to promote better theoretical base.

III.2. MEASURING RISK TO MANAGE IT

From the individual probability viewpoint, the occurrence of a traffic accident is an uncertain event. The exact time or place at which an accident will take place, cannot be determined, yet they occur at a relatively steady rate of repetition following a Poissonian probability distribution (see Chapter II). Accident frequency is one of the dimensions of road risk. The consequences of accidents and their severity in terms of material and corporal damages (see Chapter IV), should also be considered in order to thoroughly describe the road traffic risk.

Assuming that risk depends on the characteristics and states of certain elements of the road transport system, the objective of accident analysis is to identify the technical and human failures occurring in the driver/vehicle/road trio which lead to a collision. Determinants or factors which characterise this driver/vehicle/road system will influence the probability of a collision occurring. The quantitative evaluation of the influence of risk factors on the probability of accident occurrence is carried out on a statistical basis. This requires the recourse of statistical information on accidents, vehicles and those involved as well as on the risk exposure of those involved, according to the modes of transport used. For example the responsible agency has to monitor two indicators – individual and societal risk – and to compare their values to standard rates in order to detect a safety problem in case of high values. The next step is to identify the risk factors which elevate the risk using accident or risk analyses.

Once risk factors have been identified and quantified, safety and accident countermeasures must be designed to master the risk. Solutions are found in the three classical E's: Engineering, Education, Enforcement, or in some combination of safety actions, with their costs assessed.

The implementation of measures depends on considerations other than purely technical or organisational, such as political, cultural or economic aspects. Indeed, risk management has to find the 'practical' solution according to the prevailing external constraints. The weighting of advantages and costs to control risk is not purely rational and involves a complex decision process, where the objective risk is distorted by subjective evaluation.

III.3. TOWARDS RISK MODELLING

III.3.1. Different approaches in risk analysis

Due to the complexity of the road traffic system and its management, the analysis of risk necessarily involves numerous scientific disciplines, for example:

I. to treat problems of the behaviour of drivers when confronted with risks:
   A. economics (insurance, decisions under uncertainty),
   B. psychology (perception of danger, choice under uncertainty, driver training),
   C. ergonomics (information gathering, man/machine interaction, road/driver task adaptation),
   D. physiology (capacities, handicaps for driving),
   E. psycho-sociology (attitudes and judgement when confronted with risk, controls and social norms),
   F. sociology (cultural and organisational aspects, enforcement system),

II. to treat problems of accident occurrence:
   A. mechanics (traction, vehicle structure),
   B. traffic engineering (infrastructure and operations),
   C. ergonomics (understanding the road traffic system),
   D. physiology (fatigue, alcohol, physical capacities),

III. to treat problems of traumatisms during collisions,
   A. bio-mechanics (shock resistance),
   B. medicine (traumatism severity).

Two approaches can be considered in risk analysis:

1. An analytical, system-oriented approach to identify risk factors and determine their mechanisms that act on the occurrence and severity of accidents,

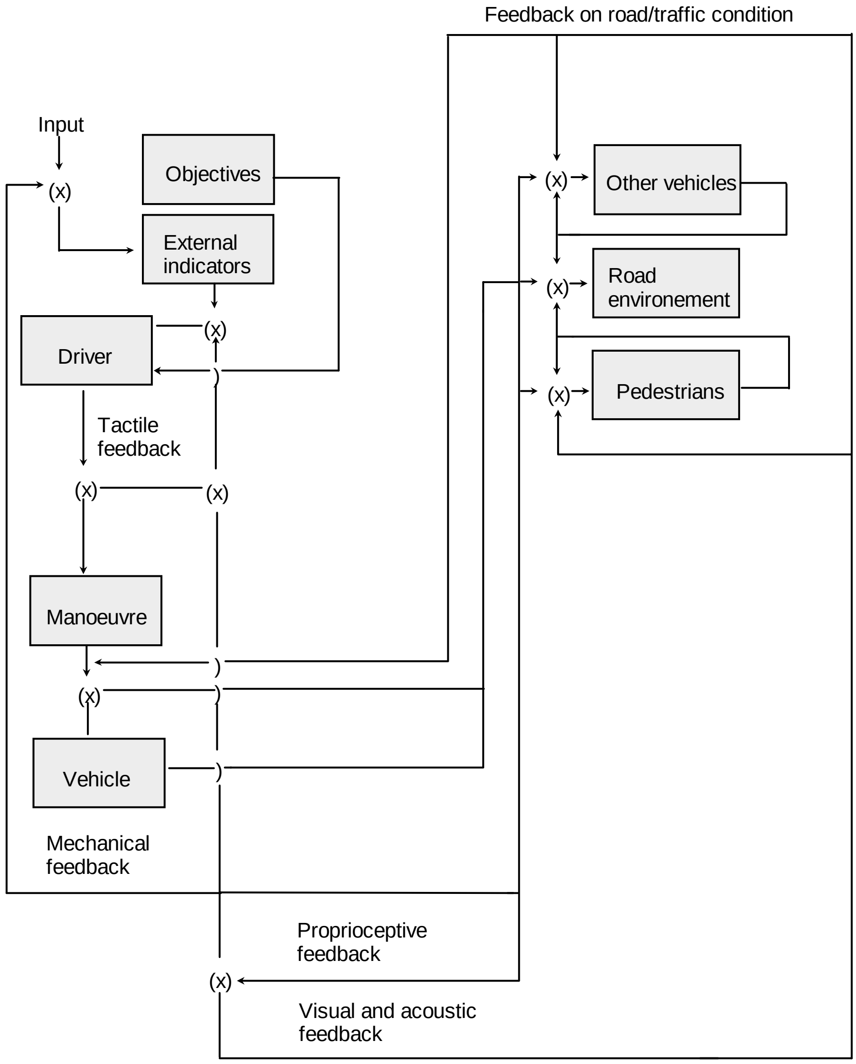
2. A quantitative approach to estimate effects using risk schemes in the form of an equation.

III.3.2. Analytical, system-oriented approaches

Regardless of the disciplines involved in analysing dangers and risks, a general concept could be established. Based on the road user's tasks and the manoeuvres required, it is possible to identify the failing elements and the vulnerable state within the system.

Analytical, system-oriented approaches aim to identify factors which lead to failures in the functioning of the system and thereby enhance risk. This procedure allows the relevant mechanisms to be determined and enables (sub)models to be established which can then be generalised and thus increase the understanding of the system. Of course, this approach needs to be done in an interdisciplinary manner and has to take into account the interaction between the components, elements and factors. Because of the complexity, it is recommended to proceed in a hierarchical process. At each level, failures can be analysed by modelling the way the vehicle/driver/road system works or fails. An example integrating the different components was suggested by Briggs in the late 60's (Hobi, 1978); see Figure III.1.

Figure III.1. **Functional diagram of a driver-vehicle-road system – taken from Briggs (Hobi, 1978*)***



III.3.3. Quantitative approaches

Once risk factors have been identified, it is important to quantify their effects on the probability of involvement or death in a road accident. This is the domain of epidemiology and reliability which involves accident and exposure data collection and gives estimates of the relative risk – using factors – by means of cohort and case/control studies. For example, an exponential curve relating the relative risk of an accident occurring to the blood alcohol concentration of the driver can be estimated from data collected by means of a case/control study where the "case" is the drivers involved in accidents and the "control" the drivers on the road.

III.4. MODELS FOR RISK ANALYSIS

III.4.1. Introduction

This section considers risk models at the level of the individual driver. Action- and risk-oriented models – focusing on the reliability of the driver – are emphasised and integrated in a general (meta) structure of human factors models. Technical models are treated in less detail than action models, as there are relatively few models affecting the individual on a non-aggregated level where the vehicle and the road infrastructure come into play.

There are numerous integrative *behavioural* models dealing with a range of variables regarding behavioural phenomena. Well known are those elaborated by Näätänen and Summala (1976), Molen and Bötticher (1987) or Shinar (1978). Michon (1989) classified the driver behaviour models as follows:

- models according to an input-output concept,
- taxonomic models referring to task analysis,
- functional models based on either technical mechanical, adaptive, motivational or cognitive mechanisms.

Comprehensive models are described in an overview study of traffic psychology by Echterhoff (1991) and in an analysis study of factors which could change road user behaviour by Echterhoff (1992).

In order to analyse the driver/vehicle/road system on a *technical* level, it is necessary to refer to science or engineering models. Vehicle dynamic models, for example, are based on mechanical equations. Technical performances of the vehicle – such as, braking, road-holding and shock-resistance – depend on scientific and technical progress by the automobile industry.

Road engineers base road and intersection design on models that consider the interaction between vehicle dynamics and the road as well as the driver's perception of the environment. Likewise, road design influences traffic flow; with the help of models, which are in fact tools of traffic theory, it is possible to optimise flow conditions and achieve acceptable safety levels.

Nevertheless, these models mainly refer to a single technical or infrastructural topic in the vehicle/road/road user system. Very few approaches deal explicitly with the interactions of the various elements in the traffic system.

III.4.2. Models related to action

The need for general structures

Given the high number of variables, factors and micro models and the different approaches (which are often unrelated), it is recommended to find an adequate general structure as a basis for modelling behavioural factors in traffic.

Aiming at a more concrete level within behavioural analysis, normative models and theories were developed comparing road user tasks – as norms or prescriptions – with observed behaviour. A distinction is made between the acceptance of formal rules and the development of informal rules. Normative models – based on the analysis of the driver's task – are especially applied for training.

The principle is that road user actions are considered the result of more or less adequate behavioural controls. Along these lines, Rasmussen (1987) presented a hierarchical model including knowledge, rules and skills. He defined eight steps within the decision process and linked them to potential errors. Reason (1994), referring to Rasmussen's model, presented a Generic Error Modelling System (GEMS) differentiating between knowledge-, rule- and skill-based errors: slips and lapses, deviating from the intended action (without being conscious) as well as unintended versus deliberate violations are integrated in the model. Based on these elements, Reason demonstrated how errors can be predicted and analysed. Ranney (1994) adapted his classification of driving tasks according to Hale et al. (1990) – see Table III.1.

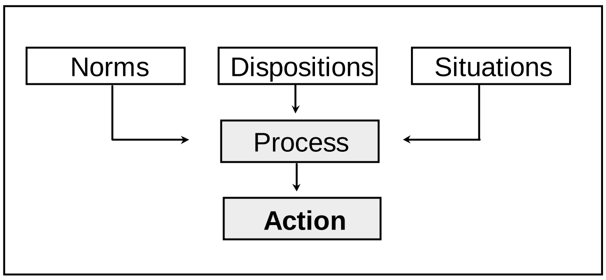
Table III.1. **Classification of driving tasks (Ranney, 1994)**

	Strategic	**Tactical/Manoeuvering**	**Operational/Control**
Knowledge	Navigating in unfamiliar areas	Controlling skid	Novice on first lesson
Rule	Choice between familiar routes	Passing other vehicles	Driving unfamiliar vehicle
Skill	Route used for daily commuting	Negotiating familiar intersection	Vehicle handling on curves

Besides these elements, it is recognised that dispositional concepts – the capacity of the driver which determines his/her behaviour in any given situation – and situational concepts – the influence the outside environment may have on behaviour – certainly play an important role.

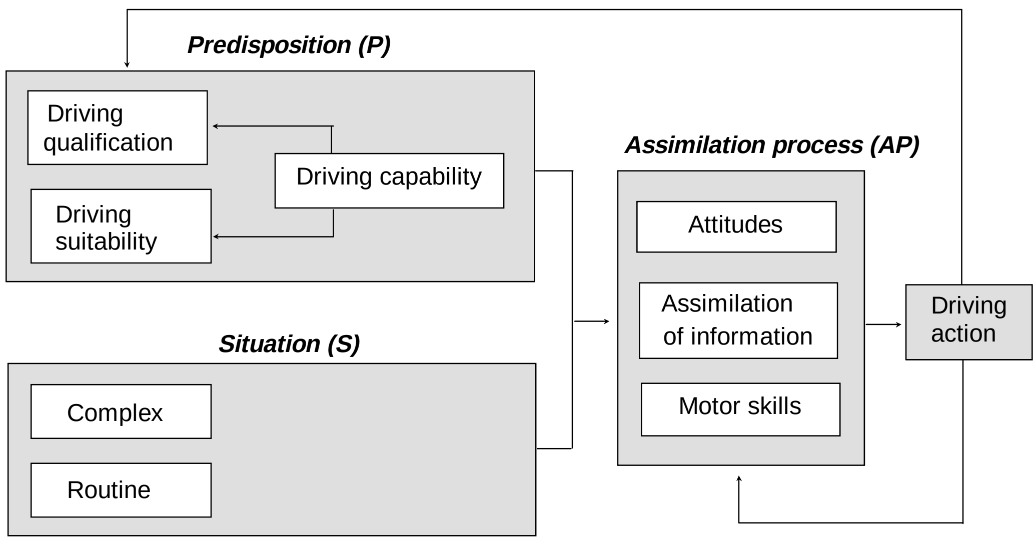
It goes without saying that a global view of these concepts is indispensable as presented with the help of Figure III.2. According to the researcher's perspective, the emphasis is on one or other of these concepts. Thus, some concepts are focused on the overview and therefore relatively simple, – as for example in Figure III.2 – or more complex as for example the model of Näätänen and Summala (1976).

Figure III.2. **Determining elements on action**



More details between the different elements called human factors and their interrelationships, are given in the overview meta-model of Figure III.3. It is a ‘map’ describing important psychological elements of road users which explains the behavioural phenomena observed in certain traffic circumstances. The advantage of these models is that they take into consideration various major psychological dimensions, thus allowing for the analysis of behavioural determinants of the human sub-system. However, interactions between subjective variables (e.g. “driver”) and objective variables (e.g. “road”, “vehicle”) are not integrated therein. It is possible to explain behaviour as a function of the most important elements, taking different levels of behavioural observations as a general model. The driver’s predispositions and his/her assimilation process should be taken into consideration (as well as his/her cognition of the situation). The model is nothing more than a programme, but it allows the factors involved to be evaluated and the interactions within the subsystem “road user” to be determined. Based on these three observance levels, models of action can be established which take into account the characteristics of driving. The theoretical reference frame for the driver's action can be described at different levels. It can be applied for four or two wheel drivers but also to pedestrians which encounter traffic when crossing the street.

Figure III.3. **Connections between predisposition (P), situation (S), assimilation process (AP) and driving action (A); Huguenin (1988*)***



Factors at the predispositional level

The predispositional level could be interpreted as consisting of three elements:

1. *Driving suitability: Psychological and physical predisposition of the individual to drive a car*

Here, theories of accident proneness are included (see Chapter II for theoretical background). The human factor plays a major role in driving, either as a factor of errors, or as a factor of reliability – thanks to the human capacity to compensate for errors. In many studies (see Ranney's review 1994), researchers explored the relationship between a person’s involvement in a traffic accident and the presence or absence of certain permanent factors of the individual (e.g. visual perception, selective attention, reaction time). The methodological principle is to correlate, among a sample of drivers, accident evaluation with quantitative variables taken from psychological tests. Positive correlations have been revealed. For example, certain weak points in maintaining one's attention bring about a higher accident risk, while other weak points in perceptive or cognitive capacities also bring about a risk increase, albeit to a lesser extent.

These studies are becoming more pertinent, as the driving population is ageing. However, apart from ageing effects in mobilising driving faculties, consideration must also be given to risk compensation by the older driver, who will seek to reduce his/her exposure to risk by abstaining from driving at night, for instance.

Certain models – whose objective is driver selection – can include up to a hundred variables, thus running the risk of missing out on an intelligible psychological interpretation of these factor combinations (Harano et al., 1975). Accident liability models (Maycock et al., 1991; Forsyth et al., 1995), where predisposition (proneness) plays a role (see for example Häkkinen, 1958), are examples. This concept has been criticised but the relevance of the critics has its limits (Kunkel, 1973). The theoretical basis of such explanatory models is covered in Chapter II. Accident risks are unequally distributed among the driver population. Partisans of the 'accident proneness' theory in its limited version maintain – without however really proving it – that poor drivers can be identified through a specific personality trait. Automobile insurers seek to discriminate via a bonus/malus system which supposedly identifies good and bad drivers. Statistically, after a certain number of years, accident risk of a driver will converge towards its true value. The quest for other risk determinants for a driver – aside from age and sex – is developing rapidly, almost exponentially.

2. Driving qualification: Acquired psychological and physical capabilities of the individual to drive a car

Models which refer to road users' capacities, form the basis for explaining how adequate behaviour in road traffic is acquired. This concept is of prime importance, as it allows for the integration of aspects of this process which unfold in numerous circumstances. As such, the learning of driving skills, assimilation of experiences, acquisition concerning perception, anticipation and the role of memory, are included in this concept. Fuller (1984), for instance, analysed the driving task from which he developed a driver behaviour model directed at danger avoidance, based on learning theory. With classical conditioning, it can be demonstrated that there exists "a distinct preference for a delayed avoidance response – as opposed to an anticipated avoidance response – that is, a preference for the most risky behaviour". When a driver is confronted with a discriminating stimulus for a potentially dangerous event, his/her actions depend to a large extent on the rewards and punishments linked to potential responses. By means of cohort studies it is possible to separate the effect of drivers' age and experience in order to identify the relationship between risk and experience.

3. *Driving capability: Momentary ability of the individual to drive a car*

Laboratory studies have underlined the question of the reduction of a driver's suitability and qualification (i.e. driving skills, cognitive capacities). This deterioration of capability is very often due to the consumption of alcohol. Drivers with alcohol in their bloodstream represent a risk factor. The probability of drunk drivers being involved in accidents has been established for a long time, thanks to case/control epidemiological studies, by comparing exposure and risk factors in terms of alcohol concentration in drivers blood or breath (Borkenstein, 1974; Krüger, 1994). This comparison is made between two samples, taken firstly from drivers involved in accidents and secondly from other drivers on the road (Biecheler, 1985). The relative risk curve or the over-risk curve provides us with the multiplier risk coefficient of being involved in an accident depending on the alcohol level in the bloodstream. The relation can be modelled by using a log model (Allsop, 1966):

$$\log \text{ it } P \ (\text{involved in accident}) = \log \frac{p}{1-p} = \alpha + \beta \ \text{ alcohol level in the bloodstream}$$

or by using Poissonian or extra-Poissonian models (Hurst et al., 1994; see also chapter II). Similar theories are available for other drug consumption or fatigue effects (see i.e. Dionne et al., 1995).

Factors at the action level

The action level could be interpreted as consisting of three elements:

1. *Attitude as a determinant of behaviour: tendency to react in the same way to certain stimuli or irritants (the concept of subjective risk applies here; see Section III.4).*

As learning theory "is essentially based on a conceptualisation of the task of driving which implies avoidance responses acquired with potentially dangerous stimuli, as well as an application of behavioural principles which are correctly chosen for the driving situation." Michon (1989 p. 145) observed that the model proves to be hardly applicable in complex learning situations. Therefore, numerous researchers have examined the concepts of 'attitudes' and 'adaptations'. Attitudes – based on values – partially determine behaviour behind the wheel in a specific situation. This concept explains a given behaviour pattern which does not correspond to acquired behaviour which is normally observed. Often an attitude has exercised its influence and neutralised the expected action. Explanations of this phenomenon can be provided with the help of the concept of cognition and emotions. Based on Ajzen and Fishbein (1977) theories of planned behaviour and explanations for intentional and unintentional (but erroneous) behaviour has been given (Forward, 1997; Åberg, 1997).

Another class of models seeks to explore the relationship between attitudes, behaviour and accidents. Thanks to scores of questions in the form of scales reduced to a small number of factors (factor analysis), it is possible to combine these elements with individual accident rate (Parker et al., 1995; Rutter and Quine, 1996). It is also possible to correlate them to accident data collected for the sample of drivers selected (Biecheler and Moget, 1989; Audet and Marcil, 1995).

2. *Assimilation of information: a cognitive process in which objects and situations are observed and judged (the cognition of objective risk applies here; see below).*

3. *Motor skills: movements of the body and parts of the body adapted to conditions of space and time*.

Factors at the situational level

The situational level could be interpreted as consisting of two elements:

1. *Routine situations: Situations which, due to predisposition and action determinants, can be dealt with using usual behaviour patterns, i.e. without involving processes of choice and decision; actions take place in an automated way.*

2. *Complex situations: Situations which include choice between alternative responses, in the course of which the preceding action is interrupted, because a decision involving alternative actions must be made. Complex situations involve conflict: for example where unexpected (emergency) situations suddenly occur.*

Situative models concentrate on describing the situation in which the road user is found. Determining factors are analysed according to the behaviour which occurs in the situation. The most well-known approaches in this context are based on system theories, which allow the influence of a driver's environment on the way he/she drives to be evaluated. Behaviour cannot be described in general terms, but only by reference to specific situations. A general form of description, which would ultimately permit predictions, can hardly be given.

Actions (A) should be regarded as a function of the three levels, situation (S), predisposition (P) and assimilation process (AP) (see Figure III.3):

$\{A = f (S, P, AP)\}$

The situation acts as the stimulus to driving action. The assimilation process takes place based on the established predisposition, whereby driving capability must be regarded as the regulator of driving qualification and driving suitability. Attitudes, processes of information assimilation and motor skills employed in the actual situation, develop according to driving suitability and driving qualifications. Emotion, impulses and intellectual capacities also play a role here, as could the creation of risk. However, in view of the action-theory model, it could also be dispensed with and replaced by value judgements in the decision-making process. If driving capability is impaired, the influence of driving suitability and driving qualifications also change. At the action level, attention must be given mainly to the process of attitude and information assimilation.

The permanent or transitory characteristics of the vehicle, the infrastructure or traffic can be considered situational factors which affect the driving activity and the risk of accident involvement. However, at the individual driver level, it is difficult to observe the influence of variations in driving situations – which result from changes in the status parameters of the driven vehicle, the infrastructure and surrounding traffic. For this reason information on driver behaviour must be collected, not by means of questionnaires or from test track experiments, but by observing drivers under real driving conditions. While much driver psychology research has been devoted to the links between the driving variables – speed, acceleration, collision time, lateral distance, visual fixation time, – and vehicle, infrastructure and traffic characteristics, there are fewer studies which attempt to link these variables to specified individual accident risk (for example, leaving the road, collision with a vulnerable road user, rear-end collision).

Evans and Wasielevski (1982) showed that there was a positive link between the risk of accident involvement and risk-taking as defined by the time gap to the preceding vehicle on a motorway lane. A single measurement of this time gap was made for each driver, who was identified (more or less accurately) on the basis of his or her number plate. By obtaining the accident background of the driver from insurance companies it was possible to establish this link, because the variations in risk-taking between individuals are greater than the variations in an individual's behaviour during one trip. However, a continuous measurement of the time gap with the preceding vehicle would improve the ability to discriminate between short gaps which are imposed by traffic conditions and those which are voluntary.

In a later study, Wasielevski (1984) attempted modelling the interactions between the characteristics of the driver (age, sex) the vehicle (age, weight), the behaviour of the driver (speed, measured once or twice; wearing of safety belt), and the drivers past record of offences and accidents. Usually however, research into situational factors offers a cross-section which stresses only one dimension – the vehicle, the road section or the intersection – by aggregating data about individual drivers. For example, Wilde (1994) quotes Taylor's study (1964), which provides the basis for his theory of risk homeostasis, where on a road divided into sections, the average speed and galvanic skin response of twenty drivers was measured and correlated with the actual accident rate per vehicle kilometre over a two year period.

Below, a few quantitative models of risk are discussed in order to show the approach taken in identifying the technical failures connected with the human operator in the traffic system. One of the difficulties to overcome in the evaluation of risk factors such as vehicle age or the type of vehicle, is to break certain associations, for instance the vehicle-driver duo (Fontaine and Gourlet, 1994). Older vehicles are most often driven by elderly and young drivers, sports cars are most often driven by young adults. Women drivers circulate for the most part in the urban milieu. Models are often partial, as they only raise one side of the veil (driver or vehicle), while leaving the other side in the dark. Light-weight vehicles have been classified by make and type, based on the accident involvement rate established from police or insurance statistics. They hardly ever take exposure factors into consideration (mileage and wear and tear), nor risk (age/sex of driver, type of vehicle possession) to standardise the rates.

When evaluating the impact of ABS on the chances of a vehicle being involved in an accident, consideration must be given to – on the one hand – the drivers decision to buy a vehicle equipped with ABS and – on the other hand – his/her behaviour behind the wheel. By purchasing a vehicle with better braking safety performances, how will the driving habits of the owner be modified? The theory of adaptation foresees a scenario of behaviour where the driver will use the safety margin provided by ABS to drive in a more aggressive manner. Experiments conducted with groups of taxi drivers have demonstrated that the impact of ABS on accident risk is zero (Aschenbrenner et al., 1992). To take things a little further, single blind experiments must be carried out – or even double blind experiments – to eliminate the means of selection in the sample of drivers × vehicles, with and without ABS.

The risk analysis approach from the network manager's viewpoint, aims to explain accidents. Extra-Poisson-Models, as described in Chapter II, are available, in order to identify risk factors linked to infrastructure while taking into consideration volume, density and speed (average and variance), as well as the composition of traffic rate in a straight road segment (Miaou and Lum, 1993) or at cross-roads (Maycock and Hall, 1984; 1986; Brenac, 1994; Kulmala, 1995). The list of infrastructure characteristics taken into account for the models is impressive. The following can be cited:

- the presence of cross-roads or accesses,
- carriageway width,
- the nature of the shoulder (grass, gravel, asphalt), its width and its slope,
- the radius of the curve,
- the nature of the environment (built-up, woods, open area),
- vertical signalling and horizontal marking.

A number of factors must be considered, such as the influence of the width and the nature of the shoulder surface (Zeeger et al., 1988), the influence of a row of trees along the road (Lassarre, 1976), or even the distance between those trees and the pavement.

The methodological problem is that of sectioning with two strategies opposing one another: Fixed length segment as opposed to variable length segment (Shankar et al., 1995). The fixed segment must be sufficiently small (100 m) to maintain the segment's homogeneity, and sufficiently big (1,000 m) to have reasonable accident occurrences, thus avoiding accident localisation errors. The variable segment is adaptable as a function of the homogeneity required by the criteria used (traffic composition and volume, geometric characteristics). This can be further refined by dividing a segment into two sub-segments based on the direction of traffic. Should the segmentation be based on traffic, the segments can be characterised by proportions, averages or rates:

- proportion of slopes or of curves,
- average width of shoulders,
- number of cross-roads, bridges, (per kilometre).

Often, road infrastructure induce certain behaviour patterns behind the wheel, or they designed for certain types of traffic. It is therefore a delicate operation to allow for specific geometric characteristics, given their net effect. The contagious nature of behaviour comes into effect between networks of different nature, and the question of migration of accidents around a given point has always been a controversial approach (Wright and Boyle, 1987). Another example with regard to road infrastructure, is the modification of concepts according to knowledge about human behaviour. Cohen (1996), based on eye movement observations, emphasised models regarding the optimal road width. Zwahlen and Schnell (1995) were able to do the same for devising road signs. In the same sense, behavioural concepts – in analogy to ergonomics – can be model-based for understanding the steering of a vehicle by the driver on a given road section.

It is difficult to evaluate all of the impacts of traffic management measures whose aims are to regulate speed, pulse traffic flow via green waves, dispatch flow and density according to the lanes available and separate flow from different categories of users depending on those same lanes.

In static mechanical theories or fluid mechanics – using speed concepts as well as density and heterogeneity entropy – problems arise because of the scales of measuring time and space when establishing models of accident rates and variables of the state of traffic. Models can be microscopic or macroscopic. The more agitated vehicle movements are and the heavier traffic is, the greater the probability of collision. But other factors also play a role, since the accident rate curve on expressways is 'U'-shaped as a function of the hourly rate of flow (Leutzbach, 1970). Low traffic flow rates are to be found at night, accompanied by freer choice of speed, fatigue and impaired visibility. They once again point to the necessity of stratifying states of traffic in order to render them comparable in terms of driving situations and vulnerabilities. Hauer (1971), based on traffic theory, established an analogy between the 'U'-shaped curve of the vehicle's involvement rate in accidents as a function of its speed at the point of collision (Solomon, 1964), and the curve providing the passing rate as a function of the vehicle's speed on a two-lane motorway. Chosen time intervals for a driver to successfully go through an intersection (Lassarre et al., 1991) – or a pedestrian (Song and Black, 1993) – lead to results involving traffic flow and the distribution of time intervals separating two vehicles in accident risk modelling.

On the road, different modes of transport are in competition with one another, even though the Highway Code tries to regulate behaviour behind the wheel. The estimation of the influence of a variety of different vehicles on accident occurrence proves to be difficult, due to the complexity of the data gathering process on traffic flow. For example, does the presence of children in the street and on the edge of sidewalks make drivers slow down? Does the fact that drivers take risk exposure into consideration reduce the chances of an accident involving a child pedestrian? Is there an optimal mix of the various modes of transport to obtain an accident 'risk reserve' via a frequency mode, or via a minimal accident seriousness evaluation? Predicative models of accident risk exist for vulnerable road users i.e. pedestrians and cyclists; (Brüde and Larsson, 1993), but there are still only few models referring to the individual road user.

III.4.3. Risk models

Wilde (1978, 1988, 1994), Klebelsberg (1982), O'Neill (1977), Oppe (1988) and Van Der Molen and Bötticher (1988) treated a very important behavioural aspect of accident prevention: Subjective risk and the corresponding behaviour. The OECD (1990) brought together the most important data thereon and created the term ‘adaptation’. The principal idea is to ensure that human beings do not adapt their behaviour to a reduced risk level after the introduction of safety measures but, on the contrary, benefit from those measures. Mostly, the theories were conceived according to a three-dimensional schema: perception, acceptance and risk control. The question posed is whether or not the risk rate observed is due to:

- shortcomings linked to risk perception,
- inadequate acceptance of risk,
- capacity shortcomings, making the driver unable to keep a full hold on the risk taken.

Tränkle et al. (1989) showed that the three ‘gaps’ can be relevant for safety deficiencies, either uni- or multi-factorial.

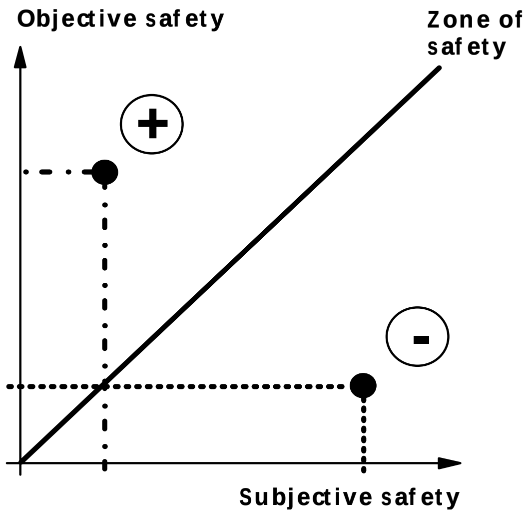
Predicting the number of accidents which will involve a given driver, can be done by calculating data on the number of accidents which have occurred in the past, or by the number of infractions committed. The whole demerit point system is based on the validity of such a relation, as well as the entire practice of the traffic conflict approach.

The ‘potential accident’ prediction is satisfying in that it is based on the total number of infractions committed, and can be improved by distinguishing different types of infractions (Smiley et al., 1989). It validity is lower when the previous number of accidents is used, due to higher variability (Peck et al., 1971). Behaviour resulting in infractions is more stable and permanent. The relationship between infractions and accidents in which the driver plays an active role is therefore reinforced.

However, “remaining” accidents (unavoidable ones) are added to the supplementary risk, and thus dilute the relationship. A question is thus posed: Should point scales, based on driver categories such as elderly drivers, be adapted given the fact that the gradient which links up the number of accidents to the total number of infractions tends to increase with age (Gerber and Peck, 1992). Most of these models have been estimated from data obtained from individual files on infractions or accidents, which do not contain information on risk exposure. Two case/control samples can be considered where traffic behaviour leading to infractions is observed (respect/non respect of a stop sign), or leading to dangerous behaviour (driving 0.8 seconds closer to or further away from the vehicle ahead). Nominative files for the vehicle in question (via identification, license plate, name), can inform about the driver’s past behaviour leading to infractions or accidents.

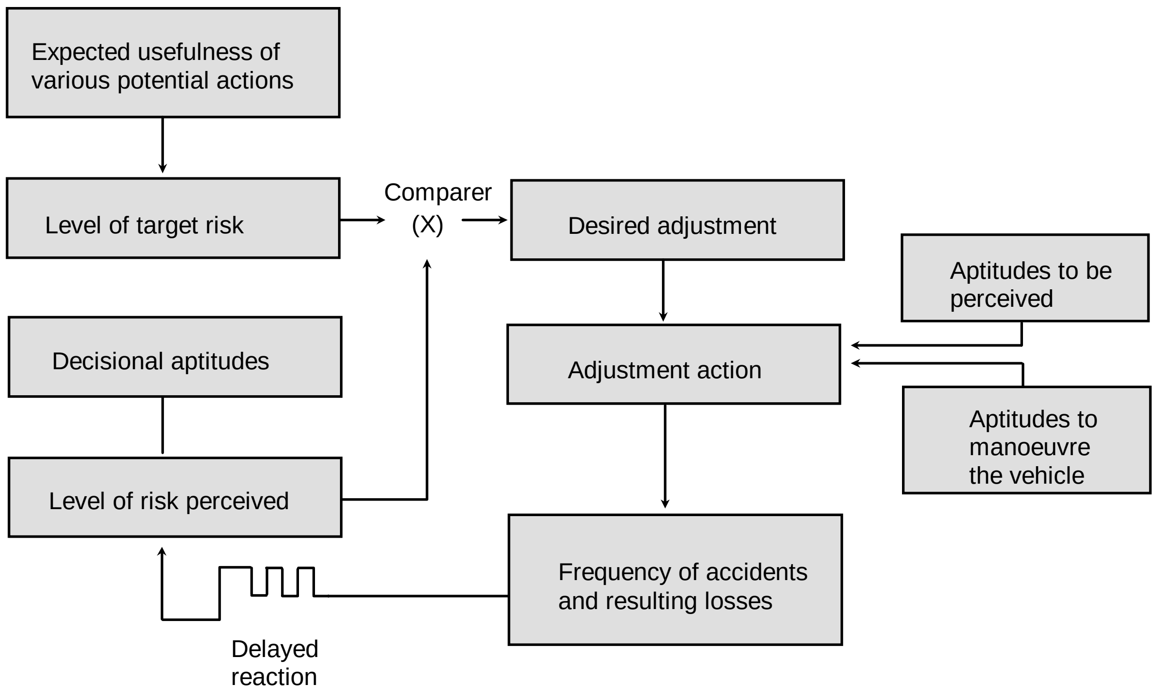
On the basis of explanations concerning objective and subjective safety aspects, Klebelsberg (1982) drafted a model along the lines of Figure III.4. The model shows that safety increases with improvements in objective safety, without commensurate increases in subjective safety; it decreases if there is an increase in subjective safety without objective safety increasing in at least the same proportion. For example, the improvement of visibility at a road junction (higher objective safety) can produce higher speeds at this crossing (because of the resulting increase in subjective safety). Under certain circumstances, accident rates may increase as a result of such safety measures.

Figure III.4. **The model of objective and subjective Safety**



The risk model which is most discussed in the field of motorway traffic is Wilde's (1988, 1994). The author poses the question, why certain drivers are willing to accept a degree of (objective) risk. According to Wilde, knowledge of risk depends on the possibility of risk perception. The objective risk perceived is evaluated and compared to the accepted risk (comparer). The result is the optimal degree of attention required. The degree of attention actually exerted depends on supplementary factors such as the driver's capacity to decide or to manoeuvre. Wilde grouped these factors together in a detailed homeostatic model (Figure III.5). Wilde's theory presents certain similarities with Klebelsberg's model. However, Wilde advances a precise dialogue: If we take measures to reduce objective risks, safety is improved as long as risk acceptance remains unaffected. In the same vein, when the objective risk remains constant, safety can improve by inciting the driver to take less chances. Nevertheless, these measures only remain efficient over a short period of time. Wilde believes that the equilibrium between estimated and accepted risks is maintained through risk homeostasis, and that safety only increases or decreases during the imbalance phase. Wilde formulates "the principle of maintaining the accident rate".... "The number of accidents in any given country only depends on the accident rate which the population is willing to tolerate, and not on the specific measures taken in other sectors of the control system – at least not over a longer period of time". (Wilde, 1978, p. 142) This principle is not applicable at the individual level, but at the level of the social system constituted by the driver population. As such, it becomes delicate to declare the theory invalid, as it is no longer possible to formulate general predictions with exactitude. "We can wonder whether the theory is of any scientific interest whatsoever (as it cannot be tested), or if it is simply false" (Haight, 1986, p. 364). Wilde quotes a considerable number of studies (including his own) to support his theory. Many among them dwell on individual behaviour after modification of one of the risk variables. All experiments and analyses quoted were not originally elaborated in order to test Wilde's theory.

Figure III.5. **Homeostatic model comparing the driver's behaviour, the accident rate and the level of target risk (Wilde, 1978)**



III.4.4. Risk compensation

Based on the risk adaptation concept (OECD, 1990), compensation mechanisms as responses to the introduction of safety measures have been described. It is obvious that these compensation effects occur, but it is not necessarily always the case. Figure III.6 depicts the different possibilities that have to be taken into consideration.

Following a – usually factually sound – definition of a problem, a measure is introduced with the purpose of improving safety in a certain part of the road traffic system. If the measure fulfils the expectations, it is referred to as a "primary effect". If it does not result in adaptation processes on the part of road users and there are no other consequential effects within the system, the effect of the measure has permanence. In the event of an accident, the accident consequences are reduced according to the bio-mechanical parameters. However, if adaptation processes are involved, i.e. there is adaptive reaction by the road user, the effect of the measure is usually influenced. This effect can be considered a "secondary effect". It will usually diminish the primary effect. In some cases adaptation leads to an increase in effectiveness. Adaptation takes several different forms:

1. *Immediate adaptation based on past learning processes.*

   Example: For safety reasons a speed limit sign is erected at a motorway exit. However, this leads to an increase in vehicle speeds because many drivers believe from experience that such speed restrictions are usually set very low.

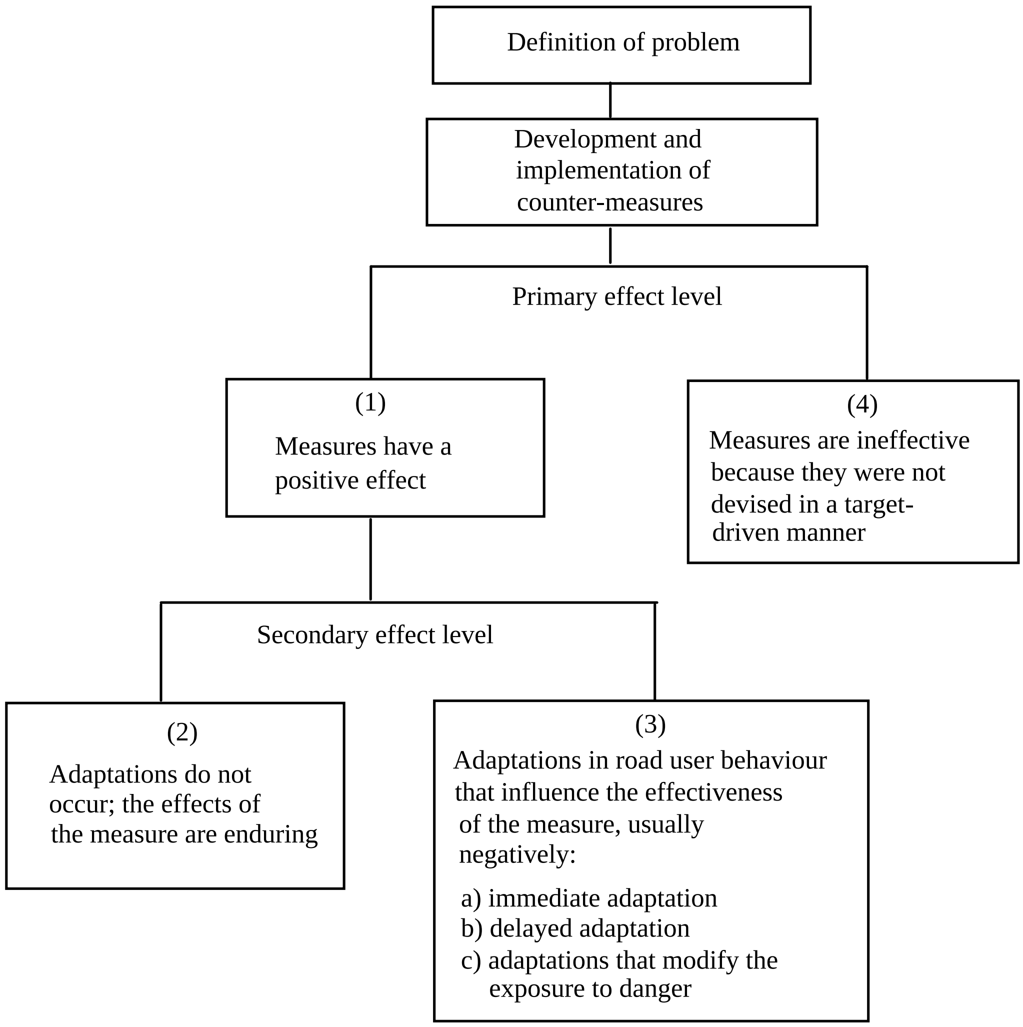
2. *Delayed adaptation as a behavioural adjustment process.*

   Example: Following the installation of public lighting it is noticed that after a while the speed on the relevant section of road increases and the safety dividend is at least partially cancelled. In place of or in addition to the intended effect an unintended effect occurs. The road user changes his behaviour in a way that was not intended when the measure was conceived.

3. *Adaptations that modify the exposure to danger.*

   Example: The parents of children that receive road safety education may be more likely to allow their children to linger in the vicinity of the road.

Figure III.6. **Differences in the adaptation process following the introduction of safety measures (schematic diagram; after Pfafferott and Huguenin, 1991)**



Finally, it is important to separate the positive measures from those where proof of effectiveness is not possible because the measures are poorly devised and cannot therefore be effective.

III.5. CONCLUSIONS

The heterogeneity of traffic and transport safety research results focusing on the individual level requires the use of more theoretical approaches to better understand and systematically use the results. Modelling facts enables the identification of the most important factors that play a role in the genesis of individual risk factors. Given a certain problem, it is important to look for a model which provides a basis to solve the problem. Multi-disciplinary and system approaches are needed to adequately cover all aspects of risk, as most scientific disciplines are mobilised.

Concerning theories and models, there are scientific fields that are both better and worse developed within traffic and transport safety. Statistical approaches are more sophisticated, in the domain of human factors; the models and theories are generally not so highly elaborated. The multitude of models should be reduced to those which are of good quality, and those that should be used as a basis for establishing traffic safety concepts.

Often extreme theoretical concepts can be found: A few are situated on a meta- (that is, on a global), others are on a micro- (that is, on a very specific) level. If so, this leads to a problematic result, as meta-theories hardly allow prognosis and micro-theories are almost irrelevant. Although there are quite a lot of safety models regarding the effect on the level of the individual, only a few are conceived as comprehensive models.

Sometimes models are transferred from one scientific field to the other. As a result of this process the problems, paradigms and hypothesis are treated carelessly or worked out less rigorously. Models should be able to help the practitioner to understand the mechanisms behind measure oriented work. Thus, they can improve the adequate design of vehicles, educational programs, infrastructure and so on as well as methodology, for example, the basis of experimental design in research.

Models should be conceived according to the interdisciplinary approach given by the driver/road/vehicle system. They should take into account the relationship and the interaction between these main elements. Regarding road users, the system and the models have to be expanded and should consider – besides car and truck drivers – two-wheelers and pedestrians as well.

The importance of designing safety measures will be underlined in Chapter IV, where the consequences are described as a function of most of the factors treated in this Chapter. Once again, this emphasises the interaction between many factors, elements or variables in the traffic safety domain. Measures have not only the intended effects – sometimes they interfere with other unforeseen factors. Models that take into account more than one or two elements will enable those responsible for safety to anticipate difficulties or even pitfalls. Examples are drivers who accept airbags but respond by wearing safety-belts less, as has been observed in Germany. In more general terms we should consider active and passive measures and their interaction or efficiency with or without compensatory effects. Similar examples could be given for the whole traffic system which has to be improved.

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CHAPTER IV APPLYING ACCIDENT CONSEQUENCE MODELS

IV.1. INTRODUCTION

The aim of this chapter is to present the different kinds of models used to describe accident consequences and to encourage their use and their further development. Models make it possible to study accident consequences and their implications and aid in the development of countermeasures to reduce injury consequences.

The consequences of accidents can be reduced by changes in the road environment, improving vehicles, improving first aid services and promoting safety equipment (see also Section IV.4) as well as influencing driver behaviour (see Chapter III). The effects of measures reducing accident consequences can be studied using two different approaches, both of which have pros and cons:

1. Aggregate consequence models give a representative general picture of the whole problem, but the data is often not as complete as in case studies, especially regarding injuries. At the aggregate level, studies can for example, examine how the consequences of an accident vary according to type of accident or how the masses of the cars involved in head-on-collisions affect accident consequences.

2. Individual level analyses and in-depth studies are continuously carried out to get more detailed information on specific accident types. The problem is usually to get enough cases and a representative database to draw general conclusions. Experimental or mathematical simulation can for example study how vehicle front geometry affects the Head Injury Criterion, which describes the chances of a pedestrian surviving a car-pedestrian accident (University of Zurich, 1986).

IV.2. METHODOLOGIES DESCRIBING CONSEQUENCES

Often, a road traffic accident is defined as an event which causes a person to be injured or at least some property to be damaged. The consequences of an accident can vary substantially. The study of accidents – without taking into account the consequences – can therefore not be very useful. For instance, the number of slight accidents is usually so large that they should dominate accident figures.

Accidents are generally classified into three or four categories according to their consequences (for example, fatal, serious, slight, none). Still the severity of an accident can be seen as a continuum divided into sub-zones by fixing some thresholds. However there is a lack of a quantitative definition of severity (Hutchinson 1986) and the thresholds of the accident categories are more or less arbitrary.

The consequences of accidents can be considered from different points of view based on:

- traffic safety or traffic safety work,
- considering accidents as a health problem,
- estimating the funds needed,
- avoiding accident consequences.

IV.2.1. Safety / accident indicators

When studying traffic safety and developing traffic safety work, it is necessary to be aware of the reference basis used: The number of all accidents, or certain injury accidents, or fatal accidents, or their number divided by some measure of exposure to accidents (Chapter I). These indicators are discussed hereunder

Often it is the number of *fatalities* that one ultimately wants to reduce. Still the effects of countermeasures are very often expressed in terms of *injury accidents*, for example, the percentage of injury accidents that can be avoided by some countermeasure. The reason for this contradiction is that traffic safety research is often based on the study of very small numbers of accidents. Indeed, in many studies, the changes in injury accidents are uncertain and the changes in the number of fatalities due to some countermeasures are even more uncertain.

When considering individual fatality risk, the risk can be expressed per some measure of exposure. The number of accidents as well as the number of fatal accidents, can be considered to follow a Poisson probability distribution curve (see Chapter II). When considering the societal risk, the risk of fatal accidents and their cluster effect has to be taken into consideration. Namely, in one accident there can be several fatalities.

The distribution of number of fatalities per one fatal accident varies by mode of transport. In aviation hundreds of people can die in one accident, which attracts great attention. Rarely are there more than 10 fatalities per one fatal accident in road traffic (Evans 1994b). Independently of the total number of deaths, accidents receive more attention, the greater the number of deaths per accident (compare aviation accidents to pedestrian accidents) (see also Box IV.1). However, because of the large variations in the definition of injury accidents and in the degree of reporting of injury accidents, international comparisons are usually carried out using fatalities.

As mentioned earlier, there is also a very large variation in injury accidents taken as a severity category. When deciding what the severity threshold of an injury accident should be, the effectiveness of an injury reducing device (e.g. using seat belt) should be defined as the percentage reduction in the proportion of injuries greater than the threshold:

$$E = 100 \times \left(\frac{x - y}{x} \right) \qquad \text{(Eq. 1)}$$

where E is the effectiveness, x is the percentage of unbelted persons who sustain injuries greater than the threshold and y is the corresponding proportion of belted persons.

Box IV.1. **Improving injury accidents vs. fatalities**

In some extreme cases, the change in fatalities can be very different from the change in injury accidents. As a hypothetical example: Motorway accidents cause 0.08 deaths per injury accident and accidents on single lane half carriageways cause 0.24 deaths per injury accident. Upgrading it to a motorway can decrease the number of injury accidents by 15 % (e.g. from 20 injury accidents to 17). At the same time the severity of accident decreases so much, that the number of deaths can be reduced even more than the number of injury accidents:

Decrease in fatalities = $0.24 \times 20 - 0.08 \times 17 = 3.44$

In this case the decrease would be 15% in the number of injury accidents but 71 % decrease in the number of fatalities.

The shape of probability distribution of injury severity is not usually very well known. It also varies in different circumstances and by types of accidents and so on. Empirically it has been found, that the effectiveness of an injury reducing device varies with the threshold of the injury (Hutchinson 1980). This problem can to some extent be tackled by using analysis techniques allowing differences in the definition of injury severity (Lai 1980).

More confusion can be caused by discussing the percentage of *avoided accidents* without specifying whether the decrease is in injury accidents or all accidents (property damage only -- PDO -- accidents included). Even these figures can be very different. Some countermeasures implemented in the interest of traffic safety, can even increase the number of slight accidents.

IV.2.2. Health / injury indicators

When discussing traffic safety as part of the health problem, the issue can be considered in different ways, for example, in terms of the number of people killed in traffic, the number of people permanently disabled or the number of days spent in hospital or unable to work. PDO accidents are insignificant when talking about health problems – possibly apart from psychological consequences in exceptional accident situations.

A fatal accident causes a greater loss of lifetime the younger the person killed is. The proportion of traffic accidents as a cause of death is larger among young people, than among old ones. A death often also causes mental suffering and social problems to the family and closest friends of the victim.

Injuries are usually classified by the International Classification of Diseases (ICD). This classification indicates the location and type of injury but not the severity of injury. The body regions most often injured and the severity of injuries are very different for different types of accidents.

The most common measure of injury severity is the abbreviated injury scale (AIS). It is internationally recognised and widely used. The AIS classification provides the severity level of an injury at a particular body region. There are six levels of injury severity in the scale ranging from level 1 – minor injury – to level 6 – maximum injuries (injuries that are currently untreatable). An overall injury severity score (ISS) has been developed for situations involving multiple injuries. The ISS criterion has a strong correlation with the survival rate of injured persons, but the relationship between ISS and severity of disability at discharge from hospital is not monotonic (Guria 1990).

ISS does not indicate the consequence of the injury in terms of long-term impairments or disabilities. The long-term consequences of injuries are described by Injury Impairment Scale (IIS). It ranges from 0 – no long term impairments – to 6 – impairment level precludes any useful function. Other approaches which have been used to evaluate the level of impairment are Quality Adjusted Life Years (QALY) and the Health Utility Index (Guria 1993).

In addition, the time spent in institutional care is another way of describing the severity of an accident. The most severe non-fatal accidents may lead to a need for full time permanent care. From the ethical point of view, it could be argued that a fatal accident should be considered at least as severe.

IV.2.3. Monetary indicators

Accident prevention and the choice of safety measures are quite often based on costing accident consequences. The aim is to relate the change in accidents and other consequences to the costs to be invested.

The methods of evaluating the socio-economic cost of road accidents vary a lot between different countries. The cost elements usually used are medical costs, non-medical rehabilitation, lost productive capacity, human costs, damage to property, administrative costs and other costs, for example, cost of congestion (COST 1994). Note however, that part of the health loss consequences caused by accidents are generally covered by the community as a whole.

Usually the “price” of a fatal accident varies the most because it includes human costs, which can be evaluated in very different ways. The variation in the price of a fatal accident is the main reason for the differences in the results of accident cost calculations, essentially because of the weight in relation to other accidents. For example, taking the values used today in Finland, about 60 % of all accident costs in 1991 were caused by fatal accidents even though their number was only 1 % of all accidents reported to the police. Non-fatal injury accidents caused about 20 % of costs (23 % of all police reported accidents).

The AIS, mentioned above, has not been intended to serve as a scale for assessing social costs. An attempt to develop an injury cost scale has been presented by Zeidler et al. (1993).

IV.3. FACTORS INFLUENCING CONSEQUENCES

IV.3 1. Traffic elements

The involvement of different traffic elements – such as passenger cars, lorries, buses, bicycles, pedestrians – in accidents result in different probabilities of fatalities. In Sweden two percent of those injured in collisions between passenger cars die compared with more than 14 % in collisions between lorries and pedestrians (see Figure IV.1).

IV.3.2. Accident type

The severity of an injury accident varies very much depending on the type of accident (Figure IV.2). There is also a strong correlation between the severity of accidents and the road category. This correlation is probably mainly caused by differences in vehicle speeds (see Section IV.3.3). The most severe accident types are those involving high collision speeds (overtaking and especially head-on-collisions) and vulnerable transport modes (pedestrians, bicycles and mopeds).

Figure IV.1. **Proportion of deaths among injured due to the involvement of traffic elements in collisions (Sweden 1991-1994)**

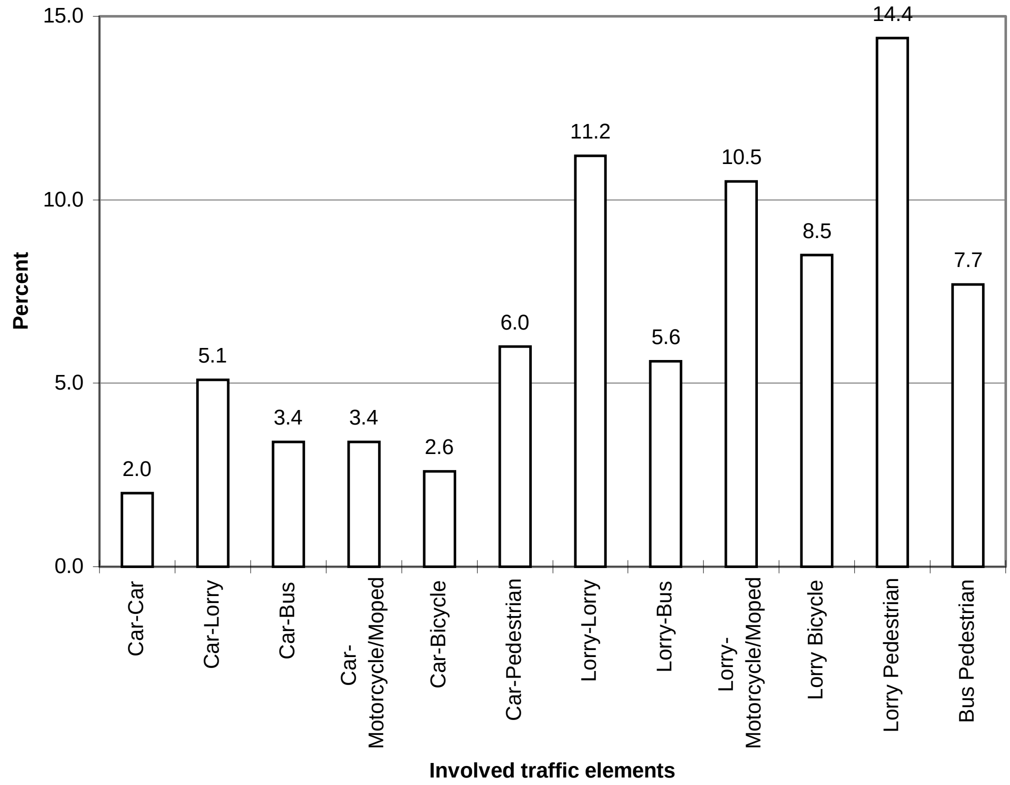
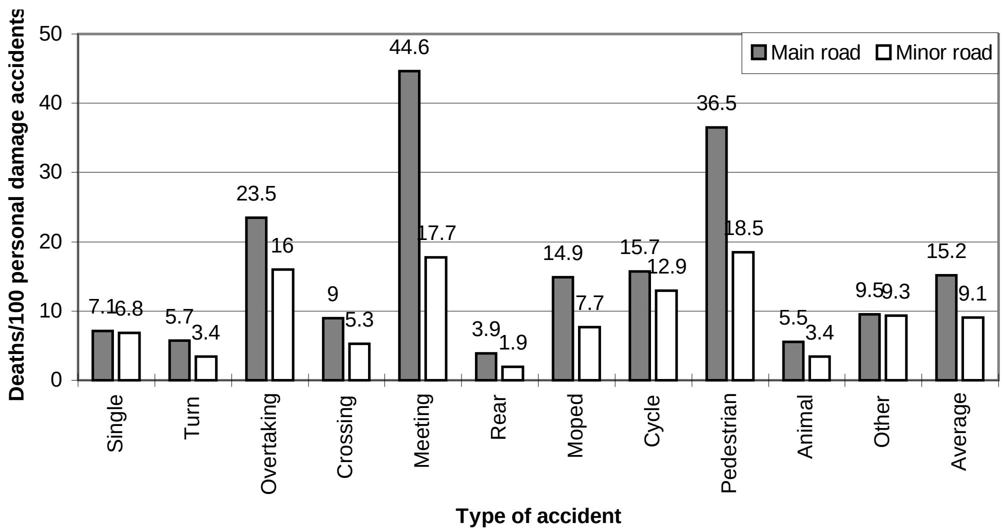


Figure IV.2. **Deaths per 100 personal damage accidents by accident type (public roads in Finland 1988-1992)**



IV.3.3. Speed

Speed is one of the most important factors affecting accident risks and especially the consequences of accidents (European Transport Safety Council 1995, Finch & al. 1994). One part of this comes directly from Newtonian mechanics:

- the distance a car needs to stop is proportional to the square of its original speed and
- the force a car causes to its counterpart in a hit is proportional to the square of its speed.

Nilsson (1984) concluded that the risk of all injury accidents seems to change by the second power of the relative change in speeds, severe injury accidents (including fatal accidents) by the third power and fatal accidents by the fourth power of the relative speed change. The background was that the empirical results proved to a large extent to be adaptable to the physics law that

$$\text{kinetic energy} = \text{mass} \times \frac{\text{speed}^2}{2}$$

on the basis of two complementary hypotheses:

1. The probability of an injury accident in the road system being reported to the police is proportional to the square of the speed v^2 – the kinetic energy

2. The probability of a fatal accident resulting from a personal injury accident is also proportional to the square of the speed v^2, which means that the number of fatal accidents is proportional to the fourth power of the speed v^4.

The speed - safety calculation models presented by Nilsson are shown in Box IV.2 and two examples are given.

The calculations have been used to investigate the safety effect of different measures to reduce the speeds in different speed limit environments with and without changing the speed limit and changed speed surveillance strategies – increased use of speed surveillance or reduced tolerance interval.

At present, there are hundreds of extensive scientific studies in the world which report road safety changes as a result of changes in speed limits and thereby changes in speeds. These studies have usually been done as before and after studies (see also Section II.2 and Appendix A). Most of these are summarised in the Road Safety Handbook published by TØI of Norway. The accumulated results are reliable and only one or two of these studies have failed to clarify that increased speeds lead to poorer road safety or vice versa. In some cases, there have been no changes either in speeds or road safety.

Pasanen (1991) reported that in built-up areas the effect of speed is surprisingly crucial to pedestrians' death risks. A car speed of 50 km/h causes to pedestrians a risk of death almost eight times higher than the speed of 30 km/h, which supports the results of Nilsson (see Figure IV.3).

According to time series models presented by Lassarre (1986) the effects of speed changes originate from two different phenomena, the change in the average speed and change in the deviation of speeds.

Box IV.2. **Speed/safety relationship (calculation model by Nilsson, 1984)**

Table IV.1. **Relationship between speed and safety Change in mean (median) v_0 to v_1**

Accidents (y)	Casualties (z)
Fatal accidents	Fatalities
$y_1 = \left(\frac{v_1}{v_0}\right)^4 y_0$	$z_1 = \left(\frac{v_1}{v_0}\right)^4 y_0 + \left(\frac{v_1}{v_0}\right)^8 (z_0 - y_0)$
Fatal and severe accidents	Fatalities and severely injured
$y_1 = \left(\frac{v_1}{v_0}\right)^3 y_0$	$z_1 = \left(\frac{v_1}{v_0}\right)^3 y_0 + \left(\frac{v_1}{v_0}\right)^6 (z_0 - y_0)$
All injury accidents	All injured (fatalities included)
$y_1 = \left(\frac{v_1}{v_0}\right)^2 y_0$	$z_1 = \left(\frac{v_1}{v_0}\right)^2 y_0 + \left(\frac{v_1}{v_0}\right)^4 (z_0 - y_0)$

Example 1. Speed increases from 85 to 90 km/h. Number of fatal accidents = 100 and the number of fatalities 110 at 85 km/h

$y = 1.059^4 \times 100 = 125.7$ $\qquad$ $z = 125.7 + 1.059^8\,(110 - 100) = 141.5$

increase 25.7 % $\qquad$ increase 28.6 %

Example 2. Speed reduction from 100 to 90 km/h. Number of injury accidents = 1000 and the number of injured 1500 at 100 km/h (fatalities included)

$y = 0.9^2 \times 100 = 810$ $\qquad$ $z = 810 + 0.9^4\,(1500 - 1000) = 1138$

decrease 19 % $\qquad$ decrease 24.1 %

IV.3.4. Vehicle mass

The terms internal and external risk have been used to describe the health losses of persons involved in collisions depending on whether they are in or out of the vehicle. When two cars collide, the fatality risks in them depend on the speeds of the cars but also the masses of the cars.

The severity of a collision can be measured by the change in speed that a vehicle undergoes as its consequence (Evans 1994a). According to Newtonian laws in a head-on collision the changes in the speeds of cars depend on their mass ratio as follows:

$$\frac{\delta v_1}{\delta v_2} = \frac{m_2}{m_1} = \mu \qquad \text{(Eq. 2)}$$

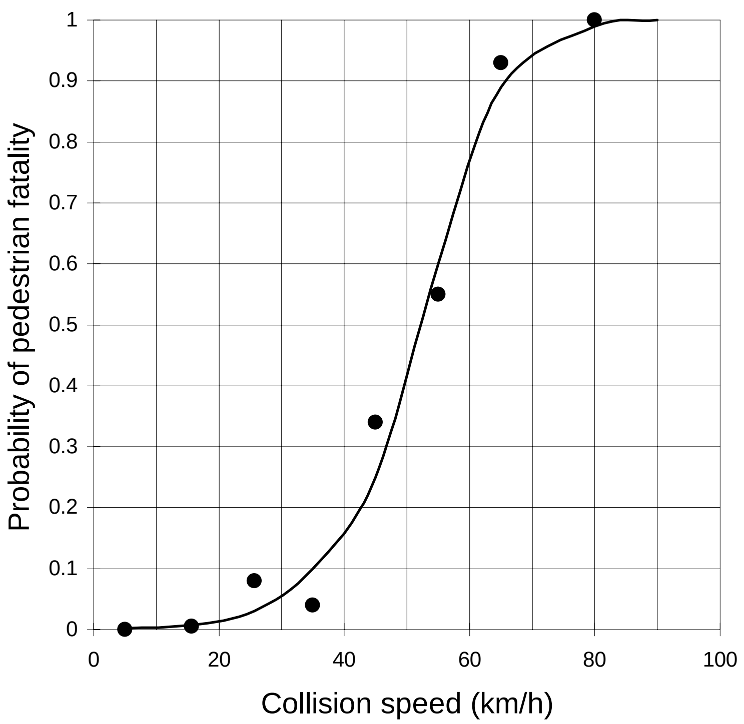
where δv_1 and δv_2 are the changes in the speeds of the cars and m_1 and m_2 are respectively the masses of the cars ($m_2 > m_1$, thus μ>1).

According to empirical studies, supported by theoretical calculations, the ratio, R, of the driver fatalities in the lighter compared to in the heavier car can be calculated by:

$R = \mu^u$ (Eq. 3)

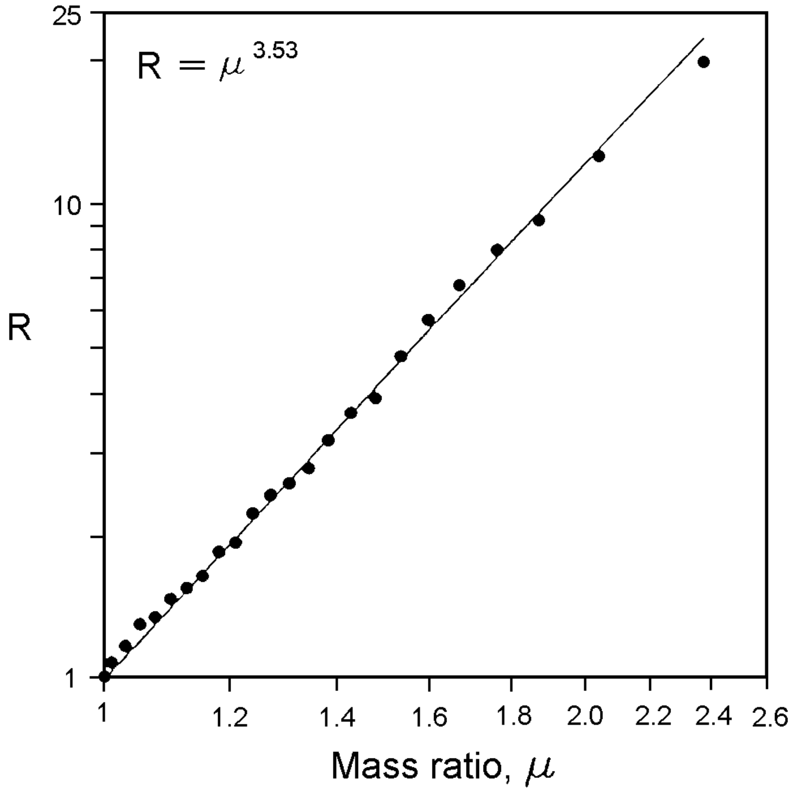
where μ is the ratio of masses defined in equation 2 and u can be empirically fitted to different sets of accidents. When fitted to data of all two-car collisions in Fatal Accident Reporting System (FARS) 1975-1989, u was estimated to be 3.53±0.03 (0.03 is one standard error) (Figure IV.4). When calculating respective ratio for injuries, the fitted values of u have been a little bit smaller than for fatalities but still quite high – 2.2 to 2.6 – (Evans 1994a).

Figure IV.3. **Fatality probability of pedestrians involved in accidents with cars with different collision speeds. Black spots are results from different case studies (Pasanen 1991)**



Using Figure IV.4 it can be evaluated that e.g. the risk R in a 900 kg car compared to the risk in a 1800 kg car when these cars crash into each other is very high, 11.6. Figure IV.4 implies, that when two cars of the same mass crash into each other, their fatality risk is equal. It has been demonstrated that their risk increases as the common mass of the cars decrease (Evans 1994a).

Figure IV.4. **The ratio, R, of driver fatalities in the lighter compared to in the heavier car versus the ratio, μ, of the mass of the heavier to the mass of the lighter car (two car collisions in FARS, 1975-1989) (Evans 1994a)**



IV.3.5. Age of injured

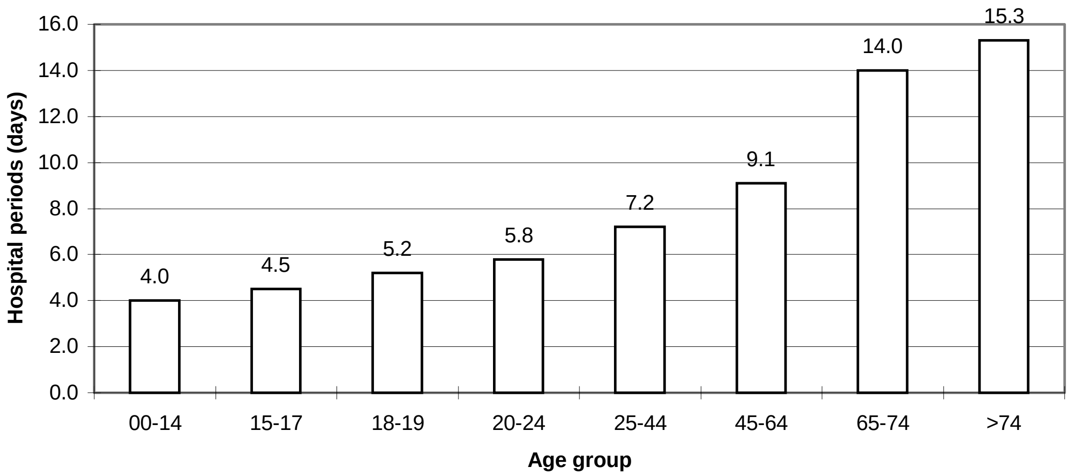
The age of the injured is one important factor for the consequences of an accident. This can be illustrated in the following figure showing the average hospital treatment period for in-patients due to traffic accidents and different age groups in Sweden 1992-1993.

The values in Figure IV.5 are adjusted for the difference in road user groups between different age groups. The treatment periods for the elderly are about 3 times higher than for young road users.

IV.4. MODELS REFERRING TO CONSEQUENCES

As noted in Section IV.3.4, the severity of a crash can be measured by the change in speed that a vehicle undergoes as its consequence. To reduce the severity of accidents, road side obstacles and equipment, vehicle engineering and protective devices (e.g. seat belts and helmets) have been successfully modelled, studied and promoted. These three domains have developed separately, but the approaches should be integrated to find an optimum. For example, probability models of hitting obstacles at a certain speed should be used together with probabilities of collision angles and consequences depending on vehicle characteristics and protective devices used.

Figure IV.5. **Average hospital treatment periods (days) for in-patients due to traffic accidents regarding age group 1992-1993 (National Board of Health and Welfare, Sweden)**



IV.4.1. Biomechanics

Biomechanical models increase the understanding and thereby prevent events which cause severe traumas to human body. The importance of biomechanics can be clarified by an example: In Sweden, 25 per cent of neck injuries caused by traffic accidents are not discovered at the time of accident (The car-pedestrian collision, 1986).

The physical limits of speed changes that the human body can bear, depend on the part of the human body that is affected during the accident. Additionally, the body regions most often injured differ over time because of changes in travel habits and safety devices used, for example, safety belts and bicycle helmets (Curia 1990, Olkkonen 1993, Thomas 1993, Norin 1995). Through experimental analyses with animals and models based on simulation it is possible to formulate some biomechanical tolerance limits, but they are not universal, because of differences between, for example, different age groups (University of Zurich, 1986).

The whole-body acceleration values of the following well-known events may give some idea of what a human body can bear (University of Zurich, 1986):

• Jump from 2 meters height (stopping distance 50 cm)	4 g*
• Parachute landing	5 g
• Maximal tolerance of air planes (emergency landing)	9 g
• Unprotected collision of head against pole (walking speed)	10-15 g
• Fall into safety net from fourth floor	10 g
• Fall from 10 meters height (impact speed more than 50 km/h) onto stone floor, according to stopping distance (30/10/5 cm)	30/100/200 g
• Severe car crash	50 g

* The unit "g" are acceleration due to gravitation (9.81 m/s^2)

Evaluations indicate that the whole body can bear no more than 40 - 80 g. Some parts of the body can bear even more, for example, brains 50 - 300 g and pelvis 50 - 80 g (University of Zurich, 1986).

Moped, motorcycle and bicycle helmets have had a positive effect in reducing severe and fatal head injuries (Olkkonen 1993). Helmets are a particularly effective safety device for bicyclists and moped users because of the speed ranges of these modes (University of Zurich, 1986).

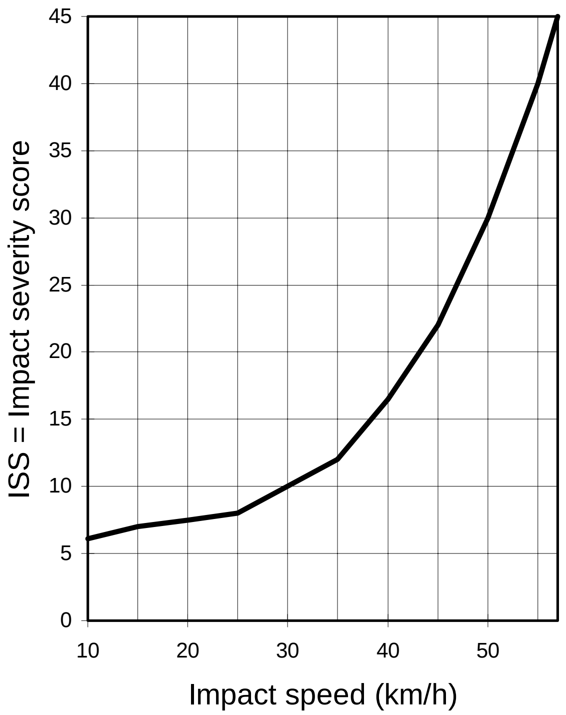
The effects of seat belts have been verified to be positive, but their magnitude depend among other variables on the type of accident and speed change of the car in the accident. The effects of air bags have not been assessed as extensively, but they have a positive effect on some types of accidents. The positive effect seems to depend on many others factors e.g. the use of seat belts (Evans 1994).

It is quite obvious and commonly accepted that the availability of first aid and medical services increase the survival rate of injured people. Verification and measurement of the magnitude of the effect is often very difficult because of a lack of adequate information and strong correlations between the variables used to describe medical resources and other variables affecting the consequences of accidents (Maio et al. 1992).

IV.4.2. Vehicle engineering

Due to vehicle improvements, the active and passive safety have been substantially increased. For example, progress in the effectiveness and use of four wheel drive, seat belts, airbags and ABS brakes could in the optimal case reduce the risks of severe accidents. But quite often due to the behavioural adaptations of drivers the safety gains have often not been fully exploited (see Chapter III). By becoming more careless, drivers lose at least one part of the safety benefits.

Figure IV.6. **Impact speed and injury severity (ISS) in car-pedestrian accidents**



Source: University of Zurich, 1986.

Driving speeds above 50 km/h in car-pedestrian accidents usually lead to impact speeds which, with car designs currently in use, cause an excessive injury severity, because the injuries increase overproportionately between 25 and 40 km/h (Figure IV.6). Improvements in vehicle design could move the curve in Figure IV.4 a little bit to the right, but because of the physical limits of human body, the change can not be expected to be very extensive (University of Zurich, 1986).

Experimental studies with dummies found that biomechanical tolerance limits known for serious injuries in impacts with car fronts are already exceeded at a collision speed of 30 km/h. Through experimental studies significant improvements have been proposed to protect pedestrians. These proposals include upper leading edges made of foamed plastics and collision displaceable bonnets (University of Zurich, 1986).

IV.4.3. Road side obstacles

Road side design can have an important effect in the severity of single vehicle accidents. Railings in front of deep roadside slopes or solid obstacles, and breakaway lighting poles can reduce the severity of single accidents.

It has been estimated in Sweden that about every fourth accident is a collision with obstacles and of these 50 % are collisions with trees. In Germany it has been estimated that 43 % of fatal single vehicle accidents involve collisions with trees.

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APPENDIX A   EFFECTIVENESS EVALUATION METHODOLOGY

This Appendix provides an overview of the techniques for conducting effectiveness evaluations with location-based (as compared to driver-based) accident data. It should be recognised that there is a much larger body of knowledge concerning the use of before-after approach for human-related safety studies. The following overview was adapted from unpublished work by Griffith. References should be consulted for more details on the methodologies and their constraints.

A.1. BEFORE/AFTER STUDY

The most common method for evaluating the effectiveness of a safety treatment is the simple "before/after" study. In a before-and-after study, there is a comparison of two statistical estimates – an estimate of the expected number of accidents after the countermeasure/program is implemented, and the expected number of accidents that would have occurred in the absence of the treatment. Generally, the data for this method are depicted as:

	Comparison	**Treatment**
Before	A	B
After	C	D

The simple before/after method uses the number of accidents within a selected period of time prior to the implementation of the treatment as an estimate of what would have occurred in the absence of the countermeasure/program. The test statistic for this method is defined as:

$$T = \frac{D - C}{\sqrt{D + C}}$$

T = test statistic.

D = number of accidents at treatment sites after treatment.

C = number of accidents at the treatment sites before treatment.

This test statistic is normally distributed asymptotically. Any value exceeding 1.96 in absolute value is considered statistically significant at the 0.05 level. One can use total number of accidents, total injuries, specific accident class (run-off-road crashes), etc. with the before/after method. While the simple before/after method was in general practice for some time, it is not now recommended because it does not account for changes or confounding factors (such as changes in driver characteristics, fleet changes, increases in exposure) that may vary from the before to the after period. The simple before/after method also does not address potential regression-to-the-mean bias in the data.

A.2. BEFORE/AFTER METHOD WITH WEIGHTS

When before/after data are available from two or more treatment locations, those data may often be combined to produce one overall estimate of treatment effect. If the treatment locations have similar characteristics and can be appropriately combined, this will provide more statistical power to the analysis increasing the likelihood of detecting treatments that are effective and improving the precision of their estimated effectiveness. Griffin (1989) has developed a weighting scheme that estimates the overall treatment effect based on the weighted average of the estimated effects at each location. In this scheme the treatment effect is estimated for each site and then weighted by the reciprocal of its variance.

$$w = \frac{1}{\left({}^{1}\!/_{A} + {}^{1}\!/_{B} \right)}$$

where

w = weighting factor
A = after-period accident count for the site.
B = before-period accident count for the site.

The before/after method with weighting scheme does not address time effects or possible regression-to-the-mean bias.

A.3. BEFORE/AFTER METHOD WITH COMPARISON GROUP

The purpose of a comparison group is to account for changes other than the treatment that may affect safety between the before and after periods. The changes in crashes at the comparison group sites are observed over the same period as the treatment sites to provide a better estimate of the what would have happened at the treatment sites had the treatment not taken place. In some cases the comparison group can be the treatment sites, but under different conditions assumed not to be affected by the treatment. For example, in the evaluation of the effectiveness of raised pavement markers (RPMs), daytime accidents at the same sites may be used as a comparison group for night-time accidents, assuming RPMs don't affect daytime safety. One must take care in selecting the comparison group to ensure that this groups is not effected by the treatment being evaluated. Two excellent articles that describe the qualities of a good comparison group are "Prediction in Road Safety Studies: An Empirical Inquiry" (Hauer et al 1991) and "Comparison Groups in Road Safety Studies: An Analysis." (Hauer 1991)

$$Odds\ Ratio = \frac{A/C}{B/D}$$

The treatment effect is measured using the odds ratio; where A/C is the odds of the before/after accidents in the comparison group and B/D is the same odds for the treatment group. The treatment effect is estimated as this ratio minus one (times 100 as a percent change) and negative values imply a decrease in accidents due to the treatment. A test statistic for assessing the statistical significance of the treatment effect derived from the odds ratio is:

$$T = \frac{\ln\left(odds\ ratio\right)}{S.D.\ \ln\left(odds\ ratio\right)}$$

where S.D. represents the standard deviation of the odds ratio. The test statistic has a standard normal distribution and is compared to normal z-values at a specified level of significance.

$$S.D.\left(odds\ ratio\right) = \sqrt{\frac{1}{A}+\frac{1}{B}+\frac{1}{C}+\frac{1}{D}}$$

In any before-and-after study, a minimum number of crashes are necessary to declare a given percent change in accident occurrence to be statistically significant. The report *A System-wide Methodology for Evaluating Highway Safety Studies* (Pendleton 1992) provides estimates of the required sample sizes.

A further extension of the before/after methodology with comparison groups is the separation of the before and after data by years. That is, one might have multiple years of before data and after data for both the treatment and comparison groups. By treating each year independently one can test the validity of the comparison group. This "test of comparability" is done by comparing the rate of change in crashes (from one year to the next) in both the before and the after periods at the treatment sites to those at the comparison sites. For more details on the test for comparability procedure, refer to *Using the Before-and After- Design with Multiple Treatment and Comparison Groups (and Multiple Before-and-After Measurements) to Estimate the Effectiveness of Accident Countermeasures* (Griffin 1992).

A.4. EXTENDED EMPIRICAL BAYES (EEB) METHOD FOR BEFORE-AND-AFTER STUDIES

A potential, problematic factor in site specific highway safety studies that the comparison group concept does not address is regression-to-the-mean bias. The bias occurs because of the non-random process of treatment site selection. The treatment site selection process generally involves selecting sites because their most recent accident histories of 1 to 3 years indicate they are the most hazardous. Because of this biased selection process, there exists a high probability that a reduction in crashes might be observed even if these sites were left untreated.

Classical statistical methods assume that the before accident history of a site is a suitable estimate of what to expect at that site in the after accident period. This may not be the case. The fact that these sites were the most hazardous could be an indication that they were experiencing an unusually high number of crashes during the observed time period. Hence, the before accident experience is inflated and is not a good estimate of what one might expect had the treatment been withheld. Significant progress has been made in developing statistical methodologies to adjust for regression-to-the-mean bias that is not controlled for through experimental design. The EEB methodology is a technique for adjusting for regression-to-the mean bias. This technique is based on the selection of a reference group to adjust for the regression-to-the mean bias. This reference group is a group of sites that might have been candidates for the treatment, but were not selected.

The development of the EEB methodology is relatively recent and applications to date have been limited. Of particular question are the characteristics and size of the reference group. Details on the EEB methodology can be found in *Application of New Accident Analysis Methodologies, Volume II: A Users Manual for BEATS* (Pendleton 1991) and *Evaluation of Accident Analysis Methodology* (FHWA).

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APPENDIX B AN EXAMPLE OF SPATIAL POISSON ANALYSIS

The purpose of this Appendix is to present examples of several spatial Poisson analyses. In particular, the models introduced Chapter II.3 are compared and their features are clarified. Pictures from a Geographic Information System (GIS) of the study area are included to display the abstract of the analysed data and the roles of GIS for spatial analysis are also discussed.

B.1. VISUALISING SPATIAL DISTRIBUTION OF TRAFFIC ACCIDENT

In spatial and temporal accident analysis, it is important to have a clear picture of accident distribution to investigate the characteristics of the accident occurrence. This picture can show locations of frequent accident occurrence and the type of accident, allowing the police or road managers to evaluate their policies. One of the powerful tools used in this process is the Geographic Information System (GIS). The GIS conveniently integrates various kinds of data on the base map, such as traffic accidents, land use, road geometry and so on. From this system, locations where many accidents occurred can be viewed and data for statistical analysis can be made easily available.

A case study of the GIS for accident analysis in Japan is introduced here. A digital road map designed for car navigation systems is used for the GIS. The study area is a suburban area in Yokohama City which is located 30 kilometres south-west of Tokyo. The area is about 60 square kilometres and the population in 1993 was approximately 250 000.

In building the GIS, data such as accident reports from the local police, land use from the urban planning map, road geometry (slope, width, curve, etc.) from the large-scale map and traffic environment from field investigation, (traffic flow in the trunk road, the number of roadside parings and traffic signals, etc.) were used. There are several databases incorporated in this GIS, The three main databases which are utilised are all-road, trunk road and local road.

In the all-road database, factors which cause accidents at black spots could be analysed. In the trunk road database, the relationship between the traffic accident occurrence and the generalised risk of traffic accident occurrence from the data of road geometry, roadside land use and traffic environment – such as roadside parking and number of pedestrians – is considered. The local road database allows the relationship between the vehicle accidents in areas of about 500m × 500m and area indices such as road density and the hierarchy of the road to be compared.

Figure B.1 shows the number of traffic accidents in the study area, totalling 1 948 from the year 1988 to 1991. The black circles indicate the accidents occurring at intersections, and the dark lines signify the accidents which occurred on road sections. The figure highlights the dangerous intersections and road sections, and it shows their frequencies simultaneously. This GIS can also display the frequency by several road attributes such as a width, slope, curvature and so on, so that the relation between the accident type and road structure can be easily identified.

Figure B.1. **The GIS picture of studied area, Morichi et al. (1995). (A circle indicates accidents at an intersection)**

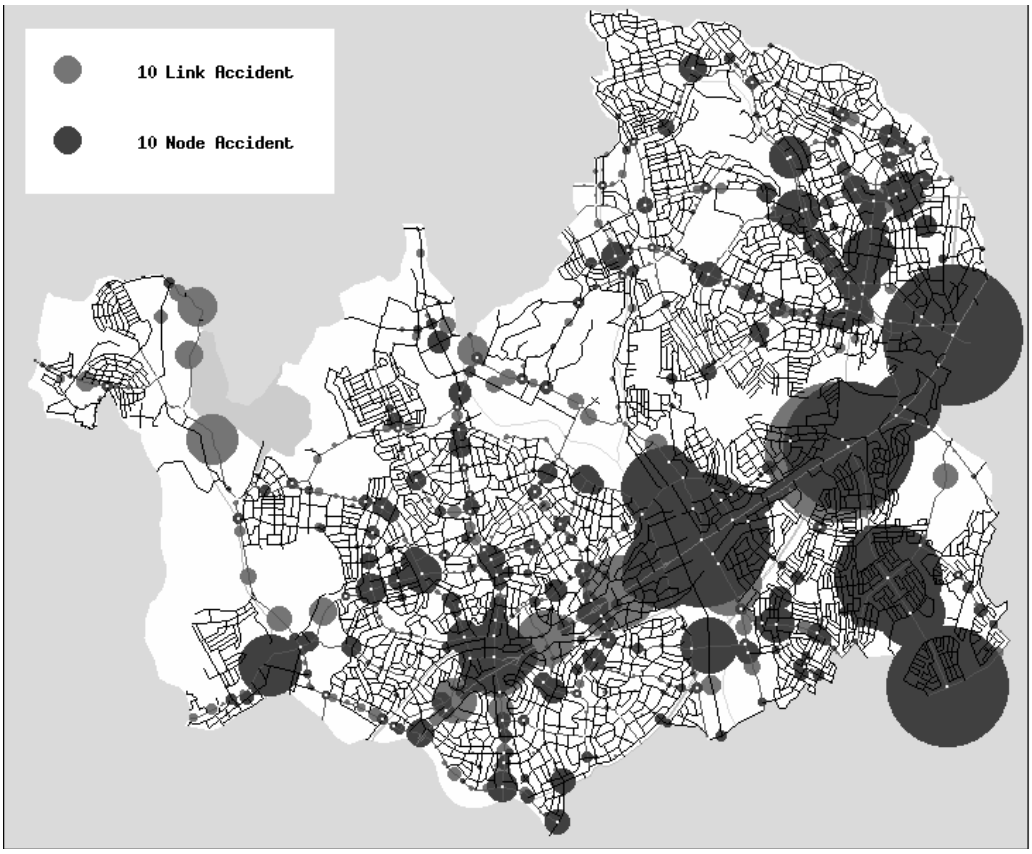

Figure B.2. **The map of locations of traffic accident occurrence, Morichi et al. (1995)**

rear end collision | crossing conflict

Another feature of GIS is to improve the manageability of accident database. Accident statistics can be updated by correctly checking the place on the screen. The GIS can play an important role in specifying and managing traffic accident data and provides an useful information infrastructure.

B.2. AN EXAMPLE OF CROSS SECTIONAL MODELLING OF TRAFFIC ACCIDENT

Traffic accidents are rare such that ordinary regression models are not suitable for application. Poisson models are useful and valid ways to express the causal relationship between traffic accidents and other observed variables. The features of the models are detailed in Chapter II.4. It is suggested that the Poisson regression model could be suitable for a rare phenomena such as traffic accident. Moreover, the negative binomial model – which is one of the generalised Poisson model -- could show a better fit to traffic accident data. The purpose of this subsection is to compare the features of each model. They were analysed using the traffic accident and road attribute data described in B.1. The model formulations are described in Chapter II.4, and the parameters of the Poisson model and the negative binomial model are estimated by Maximum Likelihood method. The goodness of fit measures of these models are introduced as follows (Fridstrøm *et al*. 1995).

R^2, R_p^2 -- The squared multiple

The ordinal R^2 measure is defined as

$$. R^2 = 1 - \frac{\sum_i \hat{u}_i^2}{\sum_i (y_i - \bar{y})^2}$$

If the y_i are Poisson-distributed with parameter λ_i and the model is perfectly specified and estimated, the expected value of $\hat{u}_i^2$ is approximately λ_i. The total residual variation would have an expected value approximately given by

$$E\left(\sum_i \hat{u}_i^2\right) \approx \sum_i \lambda_i$$

A consistent estimate of $\sum_i \lambda_i$ is $\sum_i \hat{y}_i$. Thus the amount of explained variation of a perfectly specified and estimated model would *not* exceed

$$P^2 = 1 - \frac{\sum_i \hat{y}_i}{\sum_i (y_i - y)^2} \; .$$

P^2 is in a sense the upper bound on the amount of variation that could be explained, a natural goodness of fit measure for the Poisson model could be

$$R_P^2 = \frac{R^2}{P^2} = \frac{\sum_i (y_i - y)^2 - \sum_i \hat{u}_i^2}{\sum_i (y_i - y)^2 - \sum_i \hat{y}_i} \; .$$

R^2_{PFT} -- the Freeman-Tukey R^2

Freeman and Tukey (1950) suggested the following variance stabilising transformation of a Poisson variable y_i with mean λ_i

$$f_i = \sqrt{y_i} + \sqrt{y_i + 1}.$$

This statistic is approximately normally distributed with mean

$$\phi_i = \sqrt{4\lambda_i + 1}$$

and unit variance. The Freeman-Tukey deviates ($e_i = f_i - \phi_i$) have an approximate standard normal distribution. These deviates are estimated by the corresponding residuals

$$\hat{e}_i = \sqrt{y_i} + \sqrt{y_i + 1} - \sqrt{4\hat{y}_i + 1} \ .$$

An R^2 goodness of fit measure for the Freeman-Tukey transformed variable is

$$R^2_{FT} = 1 - \frac{\sum_i \hat{e}_i^2}{\sum_i \left(f_i - \bar{f} \right)^2} \ .$$

Since the Freeman-Tukey deviates have variance one, the maximally fit obtainable in a perfect Poisson model is

$$P^2_{FT} = 1 - \frac{n}{\sum_i \left(f_i - \bar{f} \right)^2} \ ,$$

and the Freeman-Tukey goodness of fit measure for analogous to R^2_P is

$$R^2_{PFT} = \frac{R^2_{FT}}{P^2_{FT}} = \frac{\sum_i \left(f_i - \bar{f} \right)^2 - \sum_i \hat{e}_i^2}{\sum_i \left(f_i - \bar{f} \right)^2 - n} \ .$$

The models are calibrated using traffic accident characteristics such as accident between vehicle and pedestrian, rear-end collision etc. To compare the features of the three types of the models (OLS, the Poisson model and the negative binomial model) the same dependent variables are selected. The background of selection of variables are as follows.

a) *Exposure*: Exposure data is the basic variable for accident occurrence because it relates to the occurrence rate. However, sometimes it is very difficult to measure the exposure. In particular, traffic volume not on trunk roads (for example, roads in residential areas) could not be recorded exactly. This example does not include explicit exposure data because of the above reason. The study area includes one trunk road (‘Route-246’), therefore a dummy variable is introduced to indicate the difference of exposure instead of exact exposure data.

b) *Road structure*: Driving conditions are strongly affected by several road structure's attributes. It is necessary to include some road structure variables. In this study, "degree of down stream slope", "density traffic signals" and "road width" are introduced as the variables. Other attributes of road structure are curve condition or light condition or a combinations of these variable.

c) *Roadside environment*: Landscape, visibility or land-use are the principal roadside environment variables. Although, the various environmental objects affect road safety, it is however difficult to quantify the effects. Land-use attribute variable is substituted for the roadside environment ('dummy variable of commercial area').

The above variables are calculated from the GIS data. This might represent the limitations of the selection of variables in this study, but also the usefulness of the GIS to generate several variables for the regression models.

Table B.1 shows the results of these models. It can be seen that the parameters of the Poisson model and the negative binomial model are almost same, however the OLS model has different parameters. The reason is that the formulation of these models are quite different. Especially, the Poisson model and the negative binomial model are *non-linear* functions (*multiplicative* function for dependent variable) and OLS model is *linear* a function (*additive* function for dependent variable).

The goodness of fit measures of these models show almost the same values, and the relationship between these models is not clear. One of the reasons is that the model does not include appropriate exposure data. Only a dummy variable "Route 246" takes a role to express a difference of the exposure in the data, because the trunk route has the extreme huge traffic volume in the analysed roads. And this is also because of the difference of model formulations. It is difficult to judge the most appropriate model in each accident characteristics. However some models have significant over-dispersion parameters. The significance shows that the variation is larger than the specified Poisson model, and in these cases the negative binomial model could describe the distribution of accident occurrence more correctly than the other models.

The validity or rationality are outside of the range in this analysis, because the main purpose is to compare the characteristics of the regression models. The selection of appropriate variables and evaluation of the estimation result are required to make the best or better models. One of the uses of the model selection process is to specify the differences between estimated results ($\hat{\lambda} = (r,t)$) and observed value ($y(r,t)$). If the differences are displayed in GIS, many persons in charge of traffic safety as well as researchers can contribute to the process.

Table B.1. **Estimation result of regression models (( ):t-statistics)**

	using all data			vehicle/pedestrian accidents			rear-end collision			accident at a crossing		
attribute	OR	PR	NB	OR	PR	NB	OR	PR	NB	OR	PR	NB
down stream	0.0354	0.0055	0.0107	0.0108	0.0370	0.0598	-0.1811	-0.0657	-0.0577	0.0117	0.0046	-0.0094
slope (%)	(0.33)	(0.29)	(0.74)	(0.79)	(0.92)	(2.10)	(-6.35)	(-4.94)	(-3.58)	(0.13)	(0.21)	(-0.67)
density of traffic	0.0618	0.0146	0.0101	0.0007	0.0002	-0.0133	0.0153	0.0158	-0.0119	0.0857	0.0254	0.0158
signals (/Km)	(0.67)	(0.55)	(0.51)	(0.09)	(0.02)	(-1.50)	(0.94)	(0.69)	(-0.73)	(1.12)	(0.67)	(0.61)
road width (m)	0.0153	0.0057	0.0252	0.0279	0.0470	0.0369	-0.0207	-0.0042	0.0287	0.0012	0.0023	0.0359
	(0.23)	(0.31)	(2.40)	(2.00)	(2.08)	(2.50)	(-0.71)	(-0.71)	(1.45)	(0.02)	(0.09)	(2.98)
dummy var.	3.8941	0.6351	0.4713	1.0541	1.0895	0.9103	1.2028	0.7206	0.3893	2.2382	0.6261	0.4800
(commercial area)	(4.53)	(4.16)	(3.61)	(6.01)	(5.37)	(4.95)	(3.29)	(2.32)	(2.06)	(3.16)	(3.28)	(3.49)
dummy var.	12.1311	1.3040	1.1092	-0.2019	-0.2653	0.0847	9.7427	2.6733	2.3497	2.0637	0.5288	0.3460
(route 246)	(7.19)	(5.21)	(5.69)	(-0.62)	(-1.01)	(0.36)	(14.24)	(9.07)	(8.51)	(1.60)	(1.76)	(1.51)
constant	3.1940	1.1706	0.9891	0.1514	-1.2800	-0.9600	0.2992	-0.7673	-0.8778	1.9383	0.7044	0.2988
	(3.36)	(3.62)	(4.99)	(0.76)	(-3.94)	(-4.24)	(0.72)	(-1.40)	(10.40)	(2.43)	(1.43)	(1.27)
over-dispersion	-	-	1.4841	-	-	0.2033	-	-	1.0093	-	-	1.3531
parameter (ln(q))			(8.66)			(0.85)			(3.63)			(5.99)
R^2	0.167	0.157	0.159	0.094	0.099	0.084	0.388	0.449	0.438	0.033	0.048	0.040
R_P^2	0.197	0.174	0.177	0.104	0.149	0.126	0.435	0.493	0.481	0.049	0.053	0.045
R_{PFT}^2	-	0.169	0.168	-	0.417	0.413	-	0.617	0.611	-	0.030	0.040
# of links	413	413	413	430	430	430	430	430	430	417	417	417
# of accidents	1969	1969	1969	254	254	254	488	488	488	1183	1183	1183

ATTRIBUTES: OR = ordinary multiple regression model, PR = the Poisson regression model, NB = the negative binomial model

* The estimated OR model has some negative $\sqrt{4\hat{y}_i+1}$, therefore R_{PFT}^2 can not be calculated.

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APPENDIX C THE DRAG APPROACH AND RESEARCH NETWORK[10]

C.1. INTRODUCTION

This Appendix describes a family of models that explain the Demand for Road use, Accidents and their Gravity (DRAG). The models share a structure, use flexible form regression analysis, are calibrated with monthly time series data defined over a country or region, and establish a reference set of results. A brief outline of the initial model for Quebec, called DRAG-1 and the emerging network of national models is given.

C.2. A FIRST APPROACH AND MODEL: DRAG-1

C.2.1. A structure

One approach to the problem of explaining the number of road victims is to relate it, or its components (fatalities and injuries), directly to the demand for road use and to a set of other factors, as in this structure:

$$\text{VICTIMS} \leftarrow [\text{DEMAND FOR ROAD USE, OTHER FACTORS}] \qquad \textit{Risk} \qquad (1)$$

However, the approach taken in DRAG is not so direct: instead, an accounting identity is used that decomposes the number of victims into three elements, namely exposure, frequency and severity, which themselves become the objects to be explained. Thus, the number of victims is equal to the product of exposure (kilometres driven), accident frequency (accidents per kilometre) and the severity of accidents (victims per accident). This means that an explanation of the number of victims is effectively derived from the separate explanation of the three terms of the identity, as in:

[10] The authors would like to thank Mr. Marc Gaudry for supplying this Appendix based on Gaudry (1995a). The initial model was financed by the Société de l'assurane automobile du Québec (SAAQ) which supports the development of the network.

$$
\text{VICTIMS} \leftarrow \begin{bmatrix} \text{Demand for road use} & \leftarrow [\; --\;, \text{OTHER FACTORS}] \\ (\text{DR}) & (X_1) \\ \text{Accident frequency} & \leftarrow [\text{DR, OTHER FACTORS}] \\ (\text{A}) & (X_2) \\ \text{Accident severity} & \leftarrow [\text{DR, OTHER FACTORS}] \\ (\text{G}) & (X_3) \end{bmatrix} \quad \begin{matrix} \textit{Exposure risk} \\ \\ \textit{Frequency Risk} \\ \\ \textit{Severity risk.} \\ \\ \end{matrix} \qquad (2)
$$

Such a structure makes it possible to search for evidence of risk substitution among exposure, frequency and severity risk dimensions. For instance, snow, a factor included in the three groups of explanatory variables X_1, X_2 and X_3, might lead to less driving (DR decreases) and, at the reduced exposure level, to more accidents (A increases) but less severe accidents (G decreases): the net impact on the number of road victims results from the relative strength of these potentially offsetting effects.

In fact, each dimension is broken up by sub-category: type of road use (gasoline or diesel), category of accident (fatal, injury, etc.) and measure of severity (mortality, morbidity). Moreover, categories of explanatory variables include all those normally found in models: prices, vehicle availability and characteristics, network characteristics (legal regimes, modal mix, weather, ...) consumer characteristics and activity levels or trip purposes (employment, shopping, etc.).

C.2.2. An algorithm

The regression algorithm simultaneously accounts for the mathematical form of the equation with Box-Cox transformations, multiple equation-specific auto-correlation and heteroskedasticity of the residuals, and expresses results as elasticities of the expected value of the dependent variable (and of its standard error, if desired). It strikes a balance between simple fixed form structural models and pure Box-Jenkins models. It is available in TRIO (Gaudry, 1993a).

C.2.3. A data base

Monthly time-series strike a good balance between availability of data on all explanatory factors and variance of data. Higher aggregation kills variance; lower aggregation voids the structural explanation in aggregate models.

C.2.4. A reference set of results

In complex systems, it is important to gel states of the model, data and algorithms in order to guarantee flexibility in the analysis of model variants and reproducibility of results. The first model – in French – (Gaudry, 1984) contained some strong evidence of risk substitution, including strong negative relationships between alcohol consumption and the frequency and severity of fatal accidents. Further work with explicit tests of (integer and non integer) quadratic forms were consistent with the hypothesis expressed in 1984 that the risk curve associated with alcohol is J-shaped (Gaudry, 1993b, 1995b). The reference model contains large numbers of results as the equations have about 30 variables.

C.3. AN EMERGING NETWORK

C.3.1. The Quebec automobile insurance board (SAAQ) develops DRAG-2

In 1989, the Quebec automobile insurance board decided to develop an improved version of the model and assigned two professionals to this task. This has led to a series of reports on DRAG-2, including (in English) reports on kilometres driven, its explanation and a frequency of accident model (Gaudry *et al.*, 1993a, 1993b, 1993c). The full model, including severity equations is found in Gaudry *et al.* (1993d, 1994a, 1994b, 1995). These reports cover 950 pages, and are written for educated laymen and contain graphs of variables, as well as detailed explanations provided in non technical language.

C.3.2. Models for Germany (SNUS-1) and Norway (TRULS-1)

In parallel with the technology transfer from the C.R.T. to the SAAQ which has started to update DRAG-2, models were developed for Germany (Gaudry and Blum, 1993) and Norway (Fridström l997). Both models are at advanced stages of progress and full versions are expected in 1997.

C.3.3. New models for France (TAG-1), Stockholm

In France, a three-year effort to build model TAG-1, has started (Jaeger, 1994), through a collaboration between Dr. Sylvain Lassarre of the French National Institute of Transport and Safety Research (INRETS) and Universite Louis Pasteur at Strasbourg, and first results have been obtained (Jaeger and Lassarre, 1996).

Moreover, Professor Ulrich Blum of the Technical University of Dresden is putting together a network of research groups interested in building such national models. These include Professor Piet Bovy (The Netherlands), Dr. Isabelle Thomas (Belgium), Mr. Göran Tegnér and Professor Ingvar Holmberg (Sweden) and perhaps British researchers, in addition to the above groups. The network is open to individuals or group interested in the development of a regional or national model. Göran Tegnér and Vesna Loncar-Lukasic of Transek AB, Stockholm are putting the final touch to DRAG-Stockholm, a model developed as a tool to analyse the effects of a series of regional transport initiatives (called the Dennis Package) for the Stockholm region. Professor Patrick McCarthy of Purdue University has started a DRAG-type model for California.

C.3.4. Horizons 1997

Such parallel and integrated models are giving rise to a series of national reference models that is making comparative work interesting and productive. People who ask sophisticated questions about road accidents should not be surprised to learn that such efforts are needed to match the sophistication of the tools to that of the questions. The use of a common structure to answer those questions is of great interest as there appears to be no other methodology in common use across many countries. So each new member increases the relevance of work by others in the network.

In particular, this research effort involves <u>work on two-moment models</u> to explain how drivers adjust not only their accident probability but the variability of that probability, <u>work on asymmetric (quasi-quadratic) functions</u> to test within models for the impact of congestion and of the age structure of the stock of drivers on the "great mystery of 1973", i.e. the simultaneous turning point of the number of road fatalities across a wide range of countries from Israel to Japan. As about 100 000 fatalities per year occur within North America and the European Union each year, it is of major interest to find out whether the downward trend will continue and for how long.

Other parts of the research effort involve the development of new algorithms to account, across countries, for spatial correlation of residuals within models that already allow for each country equations the specific use of Box-Cox transformations with simultaneous heteroskedasticity and serial auto-correlation corrections, as generalisations of classical regression (as well as Poisson models with Box-Cox transformations) based on TRIO.

A first international conference of network participants and interested researchers is expected in 1997 or 1998, as well as a book (in English), to be published by Elsevier Science, Oxford, combining contributions of relevance to the DRAG research network.

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