INFORMATION SOCIETY TECHNOLOGIES (IST) PROGRAMME

AIDE
IST-1-507674-IP

Obtaining the functions describing the relations between behaviour and risk

Deliverable No.		**D2.3.1**	
SubProject No.	**SP2**	SubProject Title	**Evaluation and assessment methodology**
Workpackage No.	**WP2.3**	Workpackage Title	**Estimating the risk reduction potential of integrated adaptive HMI**
Activity No.	**A2.3.1**	Activity Title	**Obtaining the functions describing the relations between behaviour and risk**
Authors (per company, if more than one company provide it together)		**Samantha Jamson, Richard Batley (UNIVLEEDS), Villy Portouli, Vasilis Papakostopoulos, (CERTH/HIT), Andreas Tapani (VTI), Jan Lundgren (LIU), Yu-Hsing Huang, Erik Hollnagel (LIU), Wiel Janssen (TNO)**	
Status		**S**	
File Name:		**AIDE D2.3.1 v10.doc**	
Project start date and duration		**01 March 2004, 48 Months**	

Revision chart and history table

Version	Date	Reason
1	26/11//2005	
2	16/12/2005	Additions/changes after internal talks of authors and collegial comments
3	22/12/2005	Final edited version submitted for peer review
4	06/01/2006	Additions/changes after peer Review
5	15/01/2006	Final edited version ubmitted to EU
6	16/07/2006	Revised version after Audit Consensus Report
7	02/08/2006	Editorial revisions
8	10/08//2006	Editorial revisions after review by Project Coordinator
9	25/09/07	Minor revisions after Audit Consensus Report (2007)
10	25/10/2007	Minor editorial revisions

Table of contents

List of Figures

List of Tables

List of abbreviations and glossary

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems. Systems that interact with the driver with the main purpose of supporting the driving task on the tracking and regulating levels.
AIDE	The Adaptive Integrated Driver-vehicle Interface targeted by the AIDE IP, implementing the AIDE meta-functions
ASC	Alternative Specific Constant
Behavioural adaptation	The whole set of behaviour changes that are designed to ensure a balance in relations between the (human) organism and his/her surroundings, and at the same time the mechanisms and processes that underlie this phenomenon
CAS	Collision Avoidance System
CWA	Collision Warning
Driver distraction	Attention given to a non-driving related activity
Driving performance	The degree to which the goals associated with the driving task are attained.
Driving task	All aspects involved in mastering a vehicle to achieve a certain goal (e.g. reach a destination) , including tracking, regulating, monitoring and targeting.
HASTE	HMI and Safety of Traffic in Europe
HMI	Human Machine Interface - A set of components that govern the interaction between the user and one or more systems
ISA	Intelligent Speed Adaptation
IVIS	In-Vehicle Information System - Systems that interact with the driver with the main purpose to support tasks on the targeting and monitoring levels, or do not support driving at all.
Macro traffic simulation	Simulation model on the level of traffic streams
Micro traffic simulation	Simulation model on the level of individual vehicles
Risk	The qualitative product of the probability that something will happen and the severity of the consequences of the result. i.e. Risk = Probability of failure * Effect of failure
RUM	Random Utility Model
RUTSIM	Rural Traffic Simulator
Safety	Freedom from unacceptable risk.
SP	Stated Preference
TET	Time Exposed TTC
TIT	Time Integrated TTC
TLC	Time to Line Crossing
TTC	Time To Collision

EXECUTIVE SUMMARY

This report attempts to identify the relationships between driving behaviour and accident risk. First, a review of existing research knowledge will be provided as it is necessary to identify driving parameters that can formulate a risk assessment. An inventory of existing quantitative knowledge between longitudinal, lateral, and car-following parameters on the one hand and accident risk on the other is presented. Next, a novel approach, using Stated Preference, will be used to glean from experts an approximation of how changes in driving performance variables can affect safety. Thirdly, a field experiment specifically evaluates a methodological paradigm to estimate accident risk probabilities. Then, the potential for using microsimulation in traffic risk estimation is presented and finally, a microsimulation experiment is reported. The conclusions drawn from this work will be used as inputs to Deliverable 2.3.2 (Describing the trade-offs between behaviour and workload) and Deliverable 2.3.3 (Combining workload and behavioural effects into an overall risk reduction estimate).

The literature review reveals there to be fairly robust studies that describe the nature of the relationship between speed, speed variability and accident risk. The remaining variables relating to lane keeping and car-following are less robust, and require further investigation. The Stated Preference survey attempted to estimate the relative importance of a number of driving variables. Experts were asked to judge the various driving scenarios in terms of safety and the coefficients were used to undertake a forecast analysis. The technique proved itself to be a useful way of ranking various behaviours and more importantly combinations of behaviours, with the proviso that these rankings are based on judgement only. The driving simulator experiment showed that drivers can be manipulated to perform at varying levels and hence to engage in varying levels of risk. The microsimulation modelling work showed great promise in its application to the evaluation of ADAS. RuTSim was used to simulate ADAS equipped vehicles by manipulating the car-following model. It is possible, however, that further work needs to be undertaken in order to refine other modules of driver behaviour.

1 Introduction and background

This report attempts to identify the relationships between driving behaviour and accident risk. Typically, researchers use a range of well-established parameters with which to measure changes in driving performance. These changes are usually observable indicators of performance, such as speed (and its derivatives), lane keeping measures, headway and other surrogates of safety such as overtaking or gap acceptance behaviour.

Changes in these variables are assumed to indicate either a worsening or improvement in driver behaviour and thus safety. For example in studies of fatigue, decrements have been noted in lane discipline (O'Hanlon et al., 1995; Ramaekers and O'Hanlon, 1994; Philip, 2005). Impairment, due to illicit drugs or medication has been reported to lead to poorer car following and steering behaviour (Kay, 2000) and riskier decision making (Brookhuis et al 2004). Recent studies of driver distraction – due to the use of mobile phones, etc. - have indicated that drivers exhibit poorer braking strategies and obstacle detection and avoidance (Treffner and Barrett, 2004; Lamble et al 1999). Improvements in driving performance are gauged using similar measures; reductions in speed violations result from the installation of enforcement cameras (Keall, Povey and Frith, 2002) and feedback systems have encouraged drivers to maintain a safer headway to the vehicle in front (Fairclough, May and Carter, 1997).

Some measures, such as speed reductions, can be interpreted as being either indicative of poorer performance (as in distraction studies) or as an appropriate reaction to changes in the road environment (inclement weather or challenging road geometry). An added complication arises when the same phenomena gives rise to paradoxical changes in behaviour. This has been observed in studies of driver distraction where lane keeping performance can improve or deteriorate, depending on the type (mode) of distraction (Jamson and Merat, 2005).

Whichever variables are used to evaluate changes in driving performance, researchers should be obliged to comment on how the changes in variables might affect traffic safety (i.e. numbers of accidents). This depends not only on the direction of change, but also the size of the effects. A reduction in speed of, for example, by 3 km/h may be reported as statistically significant, but is it practically significant? What effect, if any, would such a reduction have on traffic safety in general? At this point, most research articles end abruptly, with little or no consideration for this issue. This is a reflection of the traffic safety community's scant knowledge in the area, although there are a number of variables that have received attention in recent years (see Section 3.3).

This report has five sections that attempt to provide a deeper understanding of the relationship between a number of driving parameters and safety:

1. First, a review of existing research knowledge is provided by TNO. It is necessary to identify driving parameters that can formulate a risk assessment. An inventory of existing quantitative knowledge between longitudinal, lateral, and car-following parameters on the one hand and accident risk on the other is presented.
2. Next, a novel approach, using Stated Preference, is used to glean, from experts, an approximation of how changes in driving performance variables can affect safety. This experiment was carried out by Leeds University.
3. Thirdly, a field experiment carried out by HIT, specifically evaluates a methodological paradigm to estimate accident risk probabilities.
4. Then, the potential for using microsimulation in traffic risk estimation is presented by LIU.
5. Finally, a microsimulation experiment is reported by VTI.

2 Relationship to other AIDE activities

An important part of AIDE SP 2 activities is to extend more or less conventional evaluation and assessment procedures so as to include estimates of accident risk (and preferably: risk reductions) that will be associated with the introduction of integrated and adaptive systems. Thus, it is considered not sufficient to stop the evaluation after behavioural and workload parameters have been collected, but it is realized that these results should subsequently be extrapolated to obtain 'real' accident risk in the aggregate, i.e., if an entire driving population would use the system. Only then will we be able to say what the ultimate consequences of these systems are going to be.

The risk estimation work has been concentrated in WP 2.3, comprising three interrelated Tasks, and this Deliverable is the first product of it.

It should be added that we, in WP 2.3, are obviously aware of the risk modelling work that is being done in SP 1.

The present work has profited from interactions with SP 1, in dedicated Workshops and otherwise, particularly in getting a hold on such difficult concepts like 'risk', 'risk taking', 'individual and collective risk', and 'safety'. From this the best way to express the SPs' respective roles appears to be the following:

- SP 1 focuses on (modelling of) individual risk in concrete situations in which drivers find themselves, with or without ADAS. SP 2 is looking for ways to extrapolate these individual risks to the aggregate case.
- SP 1 does modelling, while SP 2 is directed towards evaluation. With respect to risk, this means that the models that will come from SP 1 are essential to evaluation that comprises risk estimation, if only because empirical evaluation should stop at some time – we would rather not want to run simulator or instrumented-vehicle studies for the rest of our lives - and we will therefore have to rely on models at some stage. Thus, SP 1 models will provide us with material – behavioural predictions - to base an evaluation upon without actually having to run experiments.

Another clarification that is in order here is on the application of risk concepts in SP 3 vs SP 2. The distinction here is, again, that SP 3 looks at risk in a system's design stage, identifying risk as it may follow from very concrete, situation-bound interactions between a driver and an ADAS, so as to prevent these from occurring in future interactions by adequate design. SP 2, on the other hand, wants to generalize to the aggregate, so it takes a more abstract view on risk as it manifests itself in everyday driving with the system.

3 Driving parameters

3.1 Objectives

This chapter reviews empirical and other studies on the functions that are assumed to relate driving behaviour parameters, as they are usually measured in simulators and instrumented vehicles, to the accident risk that would ensue if that behaviour were shown by an entire population (the ‘aggregate’ risk). The main categories to be reviewed are (a) speed-related parameters (b) parameters describing lateral performance; and (c) parameters describing car-following performance. What will be excluded are discrete interactions between traffic participants, for example, those occurring at intersections. While these interactions are certainly risk-related they are not of the type we are looking for here, i.e., parameters that describe how a driver performs in isolation.

3.2 Methodology

A literature search has been performed in the general areas of traffic safety and behavioural indicators of risk.

3.3 Results

3.3.1 Average speed and risk

The best known functions relating average driving speed to accident risk are the ones proposed by Nilsson (e.g., Nilsson 1982, 1984, 1997). Nilsson’s functions are based on a series of naturally occurring before-and-after situations, when speed regimes were changed a number of times in Sweden during the 1970s and 1980s.
The functions are power functions of v, with the power depending on whether fatalities only are considered, or whether they also include seriously injured, or all injured, traffic participants. Figure 1 shows what the predicted effects for different accident categories are if the average driving speed in the population changes by a certain percentage.

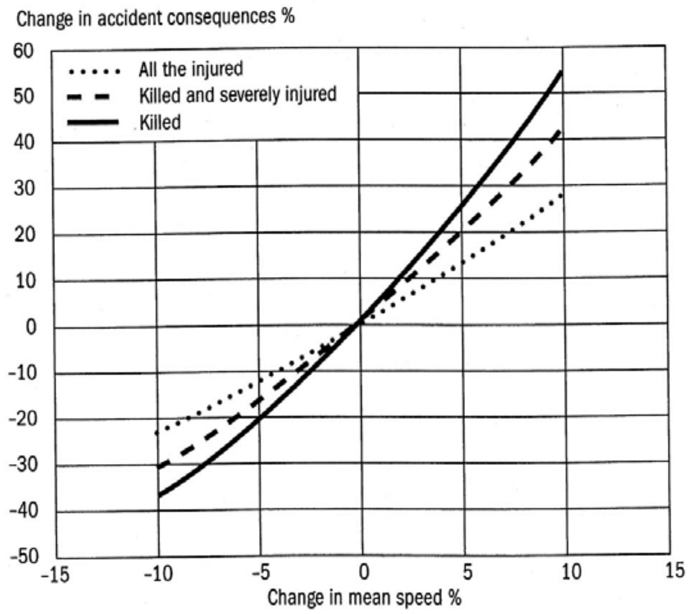

Figure 1 Speed-risk functions for different accident severities (Nilsson, 1982)

Alternative functions describing the speed-risk relationships have been proposed by Koornstra (1990). A basic distinction introduced in this model is between single-vehicle and multiple-vehicle accidents. A further interesting aspect of the model is that it includes speed variability as well (which the Nilsson model does not).

The basic expressions of the Koornstra model are:

- Risk of a fatal single-vehicle accident = proportional to v^3
- Risk of a fatal multiple-vehicle accident = proportional to $\sqrt{v}.v^2$

Roszbach and Koornstra (1991) have asked themselves whether there might possibly also exist a function relating speed variability to average speed, which would then simplify the expression for multiple-vehicle accidents. This turned indeed out to be approximately true, at least for a set of data from Dutch motorways. Here the standard deviation of speed was an almost constant fraction of 0.13 times the average speed. If that is generally true, the equation for multiple-vehicle accidents then gets an identical form to that for single-vehicle accidents (although with different coefficients): both equations then become proportional to v^3.

Salusjärvi's model (1990) also makes use of the results of 'natural' experiments, in Finland this time. His equation is again different from Nilsson's and Koornstra's. It states that if average speed changes by Δ (in km/h) the change in the risk of fatal and seriously injured (KSI) accidents will be:

Δ risk = $15(\Delta v).\sqrt{\Delta v} + 0.8$

A series of studies by the Transport Research Laboratory in the UK (Baruya, 1998; Maycock et al., 1998; Quimby et al., 1999; Taylor et al., 2000) has also looked into speed – risk functions. Maycock et al. used speed measurements on British roads in combination with self-reported accident involvement of the drivers whose speeds were measured. From this a rule-of-thumb was derived stating that a 1% increase in average speed corresponds to a 13% increase in the risk of an accident (of any type). The later Quimby et al. study, working with basically the same methodology, found an 8% risk increase per percent speed increase. And to make the TRL picture complete, the Baruya study, based on a different methodology, came to the conclusion that a 1 km/h reduction in average speed, results in a risk of reduction of between 1.5 and 3% (thus, the risk effect here is again related to an absolute speed change rather than a relative one).

Research by Finch et al. (1994), using yet another methodology (i.e. a meta-analysis of speed and risk data from a number of Western countries), came to the conclusion that a speed change of 1 km/h would change the risk by about 3%.

After comparing the different models and their outcomes for a number of cases (see Janssen, 2000) it becomes apparent that the best estimate of the change in risk that is brought about by a change in speed of 1 km/h is of the order of 5% (for fatalities). This takes into account the methodology applied in the available studies, as well as the fact that in most cases that will be encountered in behavioural research, the speed effects will probably be modest, i.e. no more than maybe 5 or 6 km/h. Over this range of effects, the difference in predictions generated by the different models are naturally restricted.

3.3.2 Speed variability and risk

Some of the models discussed in the preceding section already have speed variability in them. This does not apply to Nilsson's model. Salusjãrvi (1990) also has a separate expression for the speed variability-risk function, which has a quadratic form on (change in) speed variability, is shown graphically below. Its equation is:

Δ risk = 0.68 (Δ SD)² - 6.4 (%)

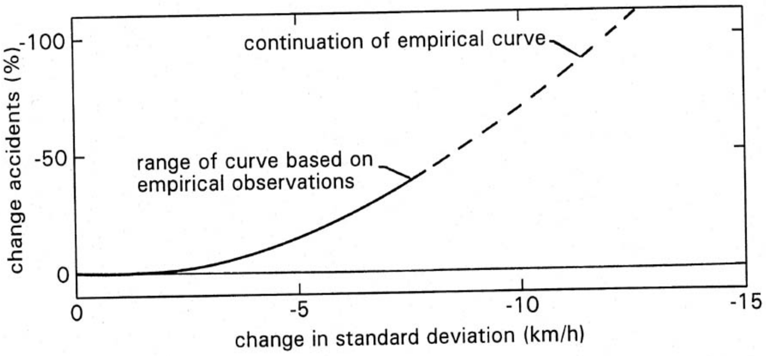

Figure 2 Relationship between speed variability and risk (Salusjãrvi, 1990)

A recent study to be mentioned here, is by Kloeden et al. (2001) in Australia. What makes the Kloeden studies special is that they differentiate their speed (variability)-risk functions according to road type. It appeared, in particular, that the functions for rural roads (80-120 km/h) were much steeper than for urban (60 km/h) roads. The functions reported are exponential in ‘v diff’, which is the difference between someone’s speed and the average speed plus an additional term in (v diff)². Thus, ‘v diff’ is a way of describing the deviation from average speed, which is mathematically different from, although obviously related to, the standard deviation of speed.

A pragmatic comparison of the different available models (Janssen, 2000) would lead us to conclude that, given the range of changes in speed variability that we can expect to find in behavioural studies, the Salusjãrvi function is the most appropriate for present purposes. Although that function is non-linear in structure (it is quadratic in the change in the standard deviation of speed), it can be approximated by stating that over a range of change in standard deviation of speed of 0-10 km/h, the associated change in accident risk will be 4-6% per km/h.

3.3.3 Lane keeping and risk

The relatively strong quantitative functions that are available for describing for the speed-risk relationships do not exist for lane keeping vs risk. What is available here as the closest ‘proxy’ to actual risk are parameters describing the risk of a lane deviation, i.e. of getting out of the lane.

An early example of this is the work by O’Hanlon et al. (1978), who extrapolated distributions of observed lane positions from an instrumented vehicle study to estimate the probability of the vehicle leaving its lane. Later studies often have actually used the proportion of time the vehicle was outside its lane itself, as a risk indicator. Of course, this approach cannot discriminate between risk levels that may be significant and that precede the situation of the vehicle actually getting outside the lane.

As a solution to differentiate between lateral risk levels before more critical and easily visible indications of risk occur, the Time-To-Line-Crossing parameter has been devised (Godthelp, 1984). On the basis of momentary speed and course parameters the TLC calculates how long it would take the vehicle to leave the lane at any given moment. A rule-of-thumb that has emerged here is that TLCs below 1s are to be considered as critical. This may then be the best we have presently to extrapolate from behaviour to risk in the lateral case, and it is proposed to use TLC as such in AIDE. However, it should be realized that even TLC is no more than a proxy, and its validity to actual risk must be deemed to be less than for the speed-risk functions discussed before.

3.3.4 Car-following parameters and risk

Besides their speed and lateral position, drivers also have to regulate their interactions with preceding vehicles. If the headways start to reduce within a following driver's reaction time (and that of the braking system itself), the probability of a collision will start to increase. There is evidence from the literature that there is a rather sharp transition point, in this respect, at a 1s following headway. Evans and Wasielewski (1982) measured car following headways in real traffic and compared this to specific drivers' accident involvement over a period of 3 years, after this single measurement on the road. The result was that those drivers who had an observed headway of under 1s were overrepresented in future accident involvement (and drivers with a headway of between 1 and 2 s were underrepresented). This is shown in the contingency table below.

Headway	No accidents	1 or more accidents	Total N
<1.0 s	326 (23.3 %)	322 (27.3 %)	648
> 1.0 s	1072 (76.7 %)	856 (72.7 %)	1928
Total	1398	1178	2576

(χ^2 = 5.5, p =. 02)

Table 1 Contingency table from Evans and Wasielewski (1982) headway study

While this result is highly interesting and also remarkable (a single measurement taken at a random moment being predictive of a driver's future accident involvement), it is not perfectly applicable for present purposes, for the following reasons:
- The relationship is statistical (correlational) in nature; and
- The relationship is of a discrete nature (i.e. headway is either below or over 1.0 s), while one would rather have continuous functions relating headway to risk.

In order to resolve these problems Monte Carlo simulation procedures have been proposed and applied by Farber (1993, 1994). These yield collision probabilities as their outcome. However, this is only half the story, since a risk estimate would also have to include the outcome (i.e. the severity) of the collision once it occurs. Figure 3 shows the results when this aspect is incorporated in the simulations (Janssen, 2000).

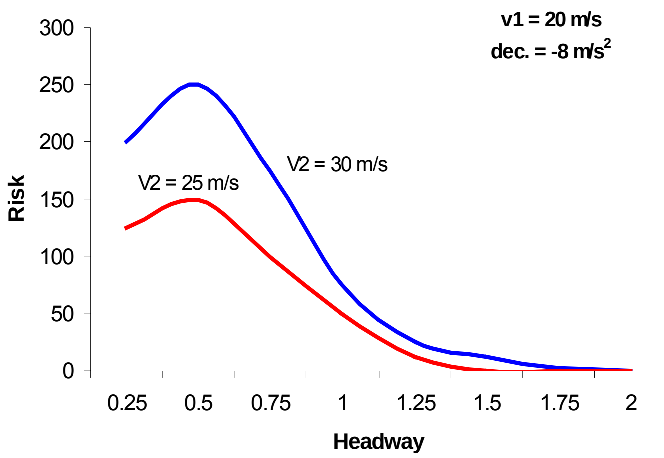

Figure 3 Relative risk of car-following at a given headway

This type of simulation is, at present, the best we have in order to estimate the risk of car-following behaviour. It is proposed that we use this procedure, or similar ones, to model the car-following risk effects of, e.g. driving with and without ADAS systems.

3.4 Conclusion

Results of a differing nature are available in the literature to model the effects of certain conventional behavioural parameters in terms of aggregate risk. We can conclude the following:

- Relatively well-developed models exist for average speed and speed variability.
- With respect to lane keeping we will have to deal with proxies, of which TLC is presently the best candidate.
- With respect to car-following we can resort to fairly elementary simulation procedures to estimate risk associated with certain headways.

4 Stated Preference study

4.1 Objectives

Whilst the research described in the section above can certainly be considered as progress, there are a number of areas that need still to be explored. Firstly, there are performance parameters that have received little or no attention regarding safety evaluation. These include lane deviations, driver awareness, overtaking and gap acceptance behaviour. Efforts to create a “red-line” for these behaviours have been limited, due to their complexity – not only in measuring them but also in their interpretation. What one person considers as “safe” overtaking, may by “risky” for another.

Secondly, how do combinations of these variables influence a safety estimate? For example if a treatment encourages lower speed but at the same time encourages the driver to follow a lead vehicle closer, how can we calculate this trade-off? Is the speed reduction considered to be “strong” enough to offset any negative effects found – or is there a threshold over which the speed reduction has to be in order to counteract any such effects?

One way of investigating such issues would be to develop a microsimulation model capable of varying the appropriate driving parameters in isolation and then in combination. An overall measure of safety would then have to be gleaned from the various combinations, using perhaps the number of near misses or actual collisions. However, this approach requires some thought as to the sorts of parameters that should be used, and also their ranges. The work described here is a first step in trying to define these scenarios and involved surveying a sample of experts using a technique known as Stated Preference. This technique allows respondents to choose between various options and make tradeoffs between them. In doing so, it allows the estimation of the relative importance of the variables that are used to characterise each option.

This technique was developed within the HASTE project. The aim of HASTE (**H**uman Machine Interface **A**nd the **S**afety of **T**raffic in **E**urope) was to develop methodologies and guidelines for the assessment of In-Vehicle Information Systems. The intention was to devise an assessment regime that was independent of the design of an IVIS, and that was based on an evaluation of driving performance while using the system, as compared with driving performance when not using the system. The first phase of the project defined the methods, metrics and scenarios in which IVIS-related safety problems are likely to occur. These metrics and scenarios were applied to the first experimental stage of the project, which attempted to establish the effect of different types of distraction imposed by an IVIS on the driving task, as well as identifying the best risk indicators for assessing IVIS use during driving. Distraction was either from a visual or cognitive ‘surrogate’ IVIS task, designed specifically to control the level of distraction in a systematic manner. The risk indicators identified in the first experimental phase were then used to work towards the development of a testing regime for IVIS that was both simple and valid. This simplified test regime was applied in a second set of experiments, for the evaluation of a series of tasks performed on some *real* IVISs while driving. Conclusions from these studies influenced the final phase of the project: the formulation of guidelines for a future test regime for IVIS, a kind of ‘cook book’, which would provide a practical testing and scoring procedure for the safety assessment of IVIS, when used during driving.

4.2 SP design

Stated preference (SP) techniques are widely used within transport research to examine and quantify decision-makers' tastes and preferences (see for example Ortúzar, 2000). Usually, SP experiments offer the decision-maker hypothetical scenarios in which a number of options are described in terms of their component features or attributes. The respondent is then asked either to rank or rate each option or, more commonly, to choose which option is preferred.

4.2.1 Implementation

The survey was developed with a combination of Java Servlets, Javabeans and JSP (Java Server Pages) atop a MySQL database. It ran as a web application in the Apache Tomcat Servlet engine. Respondents logged in to the website using a standard browser and entered their responses into dynamically populated forms which were then submitted back to the server. The server first validated the data and then stored it in the database via the Javabeans and the MySQL driver.

4.2.2 Recruitment

A database of 150 experts was created for the purposes of the survey, with expertise in the field of traffic safety or driver behaviour, as well as academics and people working in industry or policy issues. The experts were asked to provide their input (by e-mail) was on the survey, with a financial incentive of $100 and entry in a prize draw. The survey takes approximately 20 minutes to complete. After approximately two weeks, 30 responses had been collated, and following a reminder email, the final total sample was 81.

4.2.3 Variables

Five variables were chosen to reflect those most commonly used in behavioural research to evaluate driver performance. They also reflected those variables which produced significant results in the HASTE experiments.

1. Mean speed – an individual's average speed along a stretch of road, expressed as a percentage of the speed limit:

a. 50% above speed limit;
b. 20% above speed limit;
c. 10% above speed limit;
d. 5% above speed limit;
e. At speed limit;
f. 5% below speed limit;
g. 10% below speed limit;
h. 20% below speed limit;
i. 50% below speed limit.

These nine levels reflect not only increases in speed, but also decreases in speed. Travelling below the speed limit, or at least at a significantly lower speed than the surrounding traffic, has been shown to be associated with an increased accident rate (see section 3.3.1). The inclusion of these levels allowed the investigation of whether, for example, travelling at 20% above the speed limit was viewed as being equal (in terms of safety) to travelling at 20% below the limit.

2. Speed variation – how much an individual varies his/her speed along a stretch of road. This is expressed as the amount by which drivers are constantly varying their speed within 10 seconds, expressed as a % of the speed limit.

a. 0%
b. 10%
c. 20%
d. 30%
e. 50%

For example in (b), a driver would be constantly changing his/her speed by 10% of the speed limit every 10 seconds.

3. Variation in lane position – this is a measure of how much drivers deviate from their lane. It was presented qualitatively:

a. Low - driver is driving on the centre of the lane most of the time.
b. Medium - driver is deviating slightly, although he/she never exceeds the lane boundaries.
c. High - there are occasions when the driver exceeds the lane boundaries.

4. Minimum headway – an individual's minimum time headway to the vehicle in front, expressed in seconds.

a. 0.5 sec
b. 1 sec
c. 2 sec
d. 4 sec
e. 10 sec (i.e. not car following)

This measure of time headway did not include a metric of time spent at that headway. Therefore no differentiation could be made between spending one second at 0.5s headway and 10 seconds at 1s headway.

5. Driver awareness – a qualitative assessment of a driver's ability to perceive and react to changes in the environment:

a. Poor – driver is visually and cognitively distracted by his/her operation of an in-vehicle system.
b. Fair – driver is looking at the road, whilst undertaking a cognitively distracting task.
c. Good – driver occasionally glances to an in-vehicle display, but prioritises the driving task.
d. Excellent – the driver is concentrating fully on the driving task and the road environment.

This variable was introduced in order to try and reflect driver state, as this was the independent variable employed in the HASTE studies. We were particularly interested in how the experts differentiated between cognitive and visual distraction, if at all.

4.2.4 Road types

Evidence indicates that different road types have varying accident rates. For example in the UK, rural A-roads have a higher casualty rate (in terms of those killed or seriously injured) than urban roads or motorways. This trend can be observed in other European countries too. It was therefore thought appropriate to present participants with a number of different road types on which to base their ranking of the driver's behaviour. The three basic road types of urban (60 km/h), rural (km/h) and motorway were presented.

4.2.5 Scenarios

The standard procedure for designing SP experiments is to follow a fractional factorial design, where the levels of the attributes are combined in such a manner that they are not correlated with each other. This is despite the fact that with discrete choice logit models, which are the means of analysing the SP responses, independence of the input variables does not result in independence of the coefficient estimates. Furthermore, we are here employing a ranking procedure whereupon the analysis procedure will mean that even if an orthogonal fractional factorial design is used, the input variables themselves will not be orthogonal.

There was a desire to examine variables at numerous levels in order to explore non-linearities in response. Allowing for five levels yields a fractional factorial design of 25 scenarios. However, we wished to examine nine levels of speed limit. We accommodated this within the design, by allowing the last two levels within a set of five scenarios, to be the negative values of the first three speed limits. This can be clearly seen in the orthogonal design in Table 2 below. Strictly adhering to orthogonality would have required that speed was 50 in each of the first five rows, whereas we have made it 50 in the first three and -50 in the next two. The pattern is clearly repeated in the remaining rows. Whilst this does not maintain independence, we have pointed out above that the logit model used to analyse the ranked data would not anyway retain independence of the variables in its coefficient estimates. Moreover, the correlations induced between coefficient estimates were not a cause for concern.

Table 2 Skeleton Experimental Design

	Speed	Speed Variation	Variation in lane	Min headway	Awareness	Scenario
1	50	0	Low	0.5	poor	A
2	50	10	high	4	fair	E
3	50	20	high	1	excellent	E
4	-50	50	Medium	10	good	B
5	-50	30	Low	2	fair	B
6	20	10	Medium	1	fair	D
7	20	20	Low	10	poor	D
8	20	50	Low	2	fair	D
9	-20	30	high	0.5	excellent	C
10	-20	0	high	4	good	A
11	10	20	high	2	good	E
12	10	50	high	0.5	fair	E
13	10	30	Medium	4	poor	C
14	-10	0	Low	1	fair	C
15	-10	10	Low	10	excellent	E
16	5	50	Low	4	excellent	B
17	5	30	Low	1	good	B
18	5	0	high	10	fair	B
19	-5	10	high	2	poor	D
20	-5	20	Medium	0.5	fair	D
21	0	30	high	10	fair	C
22	0	0	Medium	2	excellent	C
23	0	10	Low	0.5	good	A
24	0	20	low	4	fair	A
25	0	50	high	1	poor	A

We are not only interested in the weights the experts attach to each attribute in the SP experiment, but we are also interested in their opinion if the driving represented by the scenario is safe. Whilst it is common to package up scenarios into pairwise choices, we would have had to ask not only which was safest but also whether each one was safe or not. We felt that a more straightforward procedure, and one that yields more information, would be to ask the participants to rank the drivers in safety order and to identify the point in the ranking where driving becomes unsafe. Whilst we could have simply presented each scenario and asked if it was safe or not, this would provide less information on the relative importance of each attribute than the ranking exercise.

As 25 scenarios are a lot for one driver to rank them in safety order, we separated the overall 25 scenarios into five groups of five. These are listed in Table 3. Each respondent was asked to complete the exercise three times, one for urban roads, rural roads and motorways. The pilot was studied in advance by the research team to ensure its feasibility.

Table 3 The five ranking exercises

	Speed	Speed Variation	Variation in lane	Min headway	Awareness	Scenario
1	50	0	low	0.5	poor	A
2	-20	0	high	4	good	A
3	0	10	low	0.5	good	A
4	0	20	low	4	fair	A
5	0	50	high	1	poor	A
6	-50	50	medium	10	good	B
7	-50	30	low	2	fair	B
8	5	50	low	4	excellent	B
9	5	30	low	1	good	B
10	5	0	high	10	fair	B
11	-20	30	high	0.5	excellent	C
12	10	30	medium	4	poor	C
13	-10	0	low	1	fair	C
14	0	30	high	10	fair	C
15	0	0	medium	2	excellent	C
16	20	10	medium	1	fair	D
17	20	20	low	10	poor	D
18	20	50	low	2	fair	D
19	-5	10	high	2	poor	D
20	-5	20	medium	0.5	fair	D
21	50	10	high	4	fair	E
22	50	20	high	1	excellent	E
23	10	20	high	2	good	E
24	10	50	high	0.5	fair	E
25	-10	10	low	10	excellent	E

The set of five scenarios was presented to the participant in a matrix, with an accompanying road-scene photograph and a textual description. For example in the figure below:

The road has a 60 km/h speed limit and you observe 5 drivers engaging in the following behaviour:

Driver	*Mean speed*	*Speed variation*	*Variation in lane position*	*Minimum Headway*	*Driver awareness*	**Rank**
A	At speed limit	0%	Low	2 sec	Poor	○ 1 ○ 2 ○ 3 ○ 4 ⦿ 5
B	5% above speed limit	10%	Medium	1 sec	Fair	○ 1 ○ 2 ○ 3 ⦿ 4 ○ 5
C	20% above speed limit	20%	High	4 sec	Good	○ 1 ⦿ 2 ○ 3 ○ 4 ○ 5
D	50% above speed limit	30%	Medium	10 sec	Excellent	⦿ 1 ○ 2 ○ 3 ○ 4 ○ 5
E	20% below speed limit	50%	Low	0.5 sec	Good	○ 1 ○ 2 ⦿ 3 ○ 4 ○ 5

The respondents' task was to rank the drivers (A-E) in order of safety, with 1 being the least safe and 5 being the safest. They achieved this by clicking on the buttons in the ranking column – a failsafe was included that ensured that they selected each of the options once only. In the example shown above, the respondent has indicated that Driver A is the safest, and Driver D the least safe.

Once the respondents submitted their rankings, they were then asked to provide a "safety threshold" for each scenario, i.e. the point below which driving has become unsafe which allowed us to distinguish between safe and unsafe driving. For example, whilst the respondent had provided us with rankings on the above questions, they could have thought that all drivers were behaving in an unsafe manner. This second exercise allowed them to express this.

	Mean speed	*Speed variation*	*Variation in lane position*	*Minimum Headway*	*Driver awareness*	**Rank** Where does it become unsafe?
5	At speed limit	0%	Low	2 sec	Poor	○ All are unsafe
4	5% above speed limit	10%	Medium	1 sec	Fair	○ 4,3,2,1 are unsafe
3	20% below speed limit	50%	Low	0.5 sec	Good	⦿ 3 ,2,1 are unsafe
2	20% above speed limit	20%	High	4 sec	Good	○ 2,1 are unsafe
1	50% above speed limit	30%	Medium	10 sec	Excellent	○ 1 is unsafe
						○ None are unsafe

In the example shown above, the respondent believes that scenarios 1, 2 and 3 are unsafe.

4.3 Results

4.3.1 Models

4.3.1.1 Theoretical analysis

As a methodological basis for our analysis, we adopt Neo-Classical economic theory of individual choice under certainty. The fundamental postulate of this theory is that an individual makes choices within an objective problem of maximising satisfaction or 'utility'.

Formalising this for a finite set T of alternatives (i.e. 'the choice set'), the axioms of Completeness and Transitivity establish a complete (weak) preference ordering on T, and ensure that any strictly decreasing monotone function on the ordering will induce a real-valued ('utility') function U on T that preserves the preference ordering. Thus:

$U_i \geq U_j$ if $i\,W\,j$ for all $j \in T,\ j \neq i$

where U_i is the utility of alternative i, and W denotes 'weakly preferred' (i.e. indifferent to or strictly preferred to). To interpret, the individual chooses $i \in T$ if i yields maximum utility.

Let us now consider the translation of our raw data to the above theory. The raw data consisted of a 1-5 ordering of alternatives on the basis of perceived safety, with 5 meaning the safest and 1 the least safe. This does not, however, account for the possibility that some or all drivers of the 1-5 ordering might be ranked 'unsafe'. We accommodate this possibility by introducing the safety threshold as an additional notional alternative, thereby translating the original 1-5 ordering to a revised 1-6 ordering. Note that the safety threshold could feasibly fall either within or outside either limit of the original 1-5 ordering.

With reference to the above theory, we interpret the 'safest' alternative in any set to be synonymous with the alternative 'chosen' from that set, on the basis that the safest alternative would intuitively yield the greatest utility (or least disutility). In order to exploit all possible information in the data, this interpretation was applied not only to the 1-6 ordering, but to all sub-orderings. In other words, we followed a process of 'exploding' the data into several choice observations, through repeated collapses of the 1-6 ordering, as follows:

$$T_1 = \{6, 5, 4, 3, 2, 1\}$$
$$T_2 = \{5, 4, 3, 2, 1\}$$
$$T_3 = \{4, 3, 2, 1\}$$
$$T_4 = \{3, 2, 1\}$$
$$T_5 = \{2, 1\}$$

Thus for the initial choice set T_1, rank 6 was taken to be the 'chosen' alternative, and a choice observation constructed accordingly. This alternative was then removed from T_1, giving the subset T_2. For T_2, rank 5 was taken to be the 'chosen' alternative, and a second choice observation constructed. Repeating this process for successive collapses of the choice set, five exploded choice observations were generated for each 1-6 ordering.

Finally, we devote attention to the formulation of a working empirical model that offers appropriate marriage between the theory and data. Again following convention, we adopt the Random Utility Model (RUM). Rationalising the basis for this, one should acknowledge two potential sources of randomness in the choice observations, as constructed. First, each individual was presented with 15 repetitions of the ranking exercise. Following the interpretation of Marschak (1960), randomness in RUM may derive from the repetition, in particular the facility for variability on these repetitions, of an individual's preference ordering. Second, the exercise was completed by 81 respondents. Following McFadden's (1976) interpretation, randomness in RUM may derive from the random sampling of a population of respondents, where each has differing but fixed utility functions.

Moreover, we re-couch the analysis in terms of the *probability* of choosing $i \in T$. Formally:

$$P(i|T) = \Pr\{U_{ikn} \geq U_{jkn}\} \text{ for all } j \in T,\ j \neq i$$

where U_{ikn} is the utility of alternative i in repetition k to individual n. To make this operational, U_{ikn} is dissected as follows:

$$U_{ikn} = V_{ikn} + \varepsilon_{ikn}$$

where V_{ikn} is the deterministic utility derived from alternative i in repetition k by individual n, and ε_{ikn} is the associated random utility. All that remains is to assign more specific form to each of V_{ikn} and ε_{ikn}. For the present analysis, we assume ε_{ikn} to be independently and identically Gumbel distributed. Such an assumption yields the relatively straightforward - but appealingly tractable - logit model. Formally:

$$P(i|T) = \frac{e^{\mu V_{ikn}}}{\sum_{i' \in T} e^{\mu V_{i'kn}}}$$

where μ is a strictly positive scale parameter.

For the five alternatives presented in the SP questionnaire, V_{ikn} was specified as a linear-in-parameters function of the relevant attributes, together with dummy variable interactions relating to the characteristics of the sampled individuals (in particular their occupation), and characteristics of the problem context (in particular road type). Formally:

$$V_{ikn} = \boldsymbol{\beta}\mathbf{x}_{ikn} + \boldsymbol{\delta}\mathbf{c}_n\mathbf{x}_{ikn} + \boldsymbol{\theta}\mathbf{c}\mathbf{x}_{ikn}$$

where
$\mathbf{x}_{ikn}$ is a vector of SP attributes,
$\mathbf{c}_n$ is a vector of dummy variables relating to individual n,

$\mathbf{c}$ is a vector of dummy variables relating to the problem context,
$\boldsymbol{\beta}, \boldsymbol{\delta}, \boldsymbol{\theta}$ are vectors of parameters to be estimated.

The β therefore represents the main effect of the variable in question. The extent to which this effect varies according to an individual or a problem context, is represented by δ and θ respectively.

The safety threshold or 'sixth' alternative was specified differently, simply as an alternative-specific constant (ASC). Formally:

$$V_{ikn} = \psi ASC$$

where ASC is the alternative-specific constant of the safety threshold, and ψ is a parameter to be estimated.

Under fairly general conditions, any function can be approximated arbitrarily closely by the linear-in-parameters form. This is particularly true where the levels of the variables lie in a relatively narrow range. A further attraction of the linear-in-parameters functional form is that by taking ratios of parameter estimates, one can readily infer the marginal rate of substitution. We have also generalised the linear-in-parameters form to allow for non-linearities in response by using piecewise estimation. This involves the specification of a dummy variable for each of n-1 levels of a variable with n categories. The coefficient estimates indicate the effect upon utility of the relevant categories relative to the arbitrarily omitted category.

4.3.1.2 Empirical analysis

All models were estimated using the ALOGIT software (Hague Consulting Group, 2000). The coefficient estimates of the models, along with their associated t ratios, are reported in Table 4.

Model 1
Model 1 considers the SP attributes alone, with each in its 'natural' units, i.e. as presented to respondents. Mean speed is modelled as a percentage difference - whether positive or negative - from the speed limit. Speed variation is a percentage. Variation in lane position is modelled as a dummy variable, with 'low' as the base. Minimum headway is in seconds. Driver awareness is also modelled as a dummy variable, in this case with 'poor' as the base. The final attribute is the alternative specific constant (ASC) for the safety threshold.

Table 4 Model Results

	MODEL 1	MODEL 2	MODEL 3	MODEL 4
Mean speed	-0.01702 (-15.6)			
Mean speed + 50%		-2.650 (-13.4)	-3.080 (-17.6)	-2.5716 (-11.31)
Mean speed + 20%		-1.195 (-3.7)	-1.364 (-9.1)	-0.9543 (-7.17)
Mean speed + 10%		-0.5061 (-2.4)	-0.9270 (-6.6)	-0.5221 (-5.77)
Mean speed + 5%		-0.7499 (-3.2)	-0.9270 (-6.6)	-0.5221 (-5.77)
Mean speed + 0%		-0.01201 (-0.1)		
Mean speed - 5%		-0.2896 (-1.1)		
Mean speed - 10%		-0.1598 (-0.6)		
Mean speed - 20%		-1.050 (-3.2)	-0.7736 (-5.9)	-0.8421 (-5.34)
Mean speed - 50%		BASE	BASE	BASE
Speed variation (%)	-0.01221 (-9.3)	-0.01428 (-7.7)		
Lane Variation high	-0.6162 (-12.3)	-0.8796 (-6.9)	-0.8523 (-14.7)	-0.8524 (-6.21)
Lane Variation med	-0.3877 (-6.6)	-0.1148 (-1.1)		
Lane Variation low	BASE	BASE	BASE	BASE
Min. Head (secs)	0.1307 (21.2)			
Min. Head 0.5 sec		-2.343 (-14.5)	-3.270 (-22.2)	-2.8361 (-9.84)
Min. Head 1 sec		-1.253 (-14.5)	-2.098 (-16.2)	-1.6818 (-7.59)
Min. Head 2 secs		-0.3298 (-3.2)	-0.2980 (-4.7)	-0.3309 (-3.58)
Min. Head 4 secs		-0.3753 (-2.7)	-0.2980 (-4.7)	-0.3309 (-3.58)
Min. Head 10 secs		BASE	BASE	BASE
Awareness excellent	1.273 (15.8)	1.735 (11.9)	1.698 (18.1)	1.6629 (9.47)
Awareness good	0.8015 (10.0)	1.102 (9.9)	1.176 (13.1)	1.1099 (7.30)
Awareness fair	0.6222 (9.4)	0.8613 (9.0)	0.8192 (11.5)	0.8188 (7.97)
Awareness poor	BASE	BASE	BASE	BASE
(Mean speed > limit) * ind			0.3650 (2.2)	
(Mean speed > limit) * acad			0.4949 (3.6)	
(Mean speed > limit) * politic			0.6004 (2.9)	
(Speed vary) * ind			-0.01577 (-10.0)	-0.0144 (-4.99)
(Speed vary) * acad			-0.01577 (-10.0)	-0.0144 (-4.99)
(Speed vary) * politic			-0.01577 (-10.0)	-0.0144 (-4.99)
(Lane Variation med) * acad			-0.2395 (-3.3)	-0.2120 (-3.55)
(Min. Head 0.5 sec) * urban			0.3375 (2.8)	0.3317 (2.63)
(Min. Head 0.5 sec) * ind			0.9157 (5.5)	
(Min. Head 1 sec) * ind			0.9157 (5.5)	
(Min. Head 0.5 sec) * acad			1.061 (8.1)	0.6341 (2.39)
(Min. Head 1 sec) * acad			1.061 (8.1)	0.6341 (2.39)
(Min. Head 2 secs) * politic			-0.5452 (-2.5)	
(Awareness excellent) * politic			1.359 (4.9)	0.9996 (1.68)
(Awareness good) * politic			0.7818 (4.3)	0.5615 (2.11)
(Awareness fair) * politic			0.7818 (4.3)	0.5615 (2.11)
(Awareness good) * ind			-0.3789 (-2.4)	
Unsafe	1.046 (12.1)	-0.6979 (-2.3)	-0.5069 (-4.9)	-0.5034 (-2.51)
Rho-squared w.r.t. zero	0.1169	0.2140	0.2239	0.2239

With reference to Table 4, all of the estimated parameters are significant at 1%, and seemingly with the expected signs. Note, in relation to the latter, that attributes perceived as ‘good’ (i.e. they contribute to improved safety, such as an increase in minimum headway) carry a positive sign, implying an associated increase in utility. ‘Bad’ attributes (e.g. high variation in lane, relative to low variation), in contrast, carry a negative sign.

For each of the attributes represented as dummy variables, the estimates specific to the relevant levels would appear internally consistent. Thus, the coefficient for ‘excellent’ awareness, for example, is greater than that for ‘good’ awareness, which itself is greater than that for ‘fair’ awareness; and as we have already noted, all three coefficients are positive, relative to the base of ‘poor’ awareness.

Whilst the ASC for unsafe is not amenable to direct interpretation, it does impact on the estimates of all other coefficients and it is central to ‘forecasting’ whether a driver is safe or not in a particular scenario.

The rho-squared with respect to zero offers some indication of the explanatory power of the model; its magnitude would, in this case, appear reasonable for the model type estimated.

Model 2

Model 1 gives us some confidence in the quality of the data, but yields only limited insight into its characteristics. The purpose of Model 2 was to investigate the reasonableness, or otherwise, the assumption of linearity in the continuous variables of Model 1. The investigation thus focussed on two variables; difference between mean speed and speed limit, and minimum headway.

For each variable, the prevalence of non-linearity was investigated in two ways; first, by estimating a range of non-linear but continuous functions, and second, by constructing a dummy variable for each level of the variable and estimating a step-wise function. We found that the latter was, in practice, the more revealing; we therefore restrict our reporting to that method.

The percentage difference between mean speed and speed limit was presented at both positive (i.e. mean speed greater than speed limit) and negative values (i.e. mean speed less than speed limit) in the SP design, as well as at different magnitudes. A dummy variable was constructed for each such value, with -50% taken as the base.

As regards ‘positive’ differentials, each of the estimated coefficients is significant at 1% and negative. This implies, perhaps as one might expect, that a mean speed in excess of the speed limit is considered unsafe, relative to the base. The incremental effect, furthermore, is non-linear. The coefficients relating to +5% and +10% can be seen to be insignificantly different from one another.

That aside, the size order of the estimates accords with intuition, with the coefficient for +20% greater - in absolute terms - than those for +5% and +10%, and the coefficient for +50% greater, in turn, than that for +20%. Comparison of the coefficients relating to +20% and +50% reveals them to be in rough proportion to the percentages. As regards ‘negative’ differentials, only the coefficient relating to -20% is significant, and carries a negative sign. This result would seem rather more difficult to rationalise, since it implies that -20% is considered more unsafe than -50%. What seems less controversial is the inference that a mean speed equal to, or slightly less than, the speed limit is considered safer than a mean speed in excess of the speed limit.

Minimum headway was also translated to a series of dummy variables, with separate dummies constructed for 0.5, 1, 2 and 4 seconds respectively, and 10 seconds taken to be the base.

The estimated coefficients are significant at 1% and negative; thus a lower minimum headway than the base is considered to be relatively unsafe. The relative size of the coefficients again shows some non-linearity, with the coefficients for 2 and 4 seconds not differing significantly. Otherwise, the size order of the estimates is again intuitive, with smaller minimum headways carrying larger (absolute) parameters (i.e. perceived to be less safe) than larger minimum headways.

The remaining results are largely as Model 1, with perhaps two exceptions. First, medium variation in lane is no longer significantly different from zero. Second, the rho-squared with respect to zero is noticeably increased. Since this statistic increases with the number of explanatory variables, however, it is difficult to draw a substantive verdict on the respective fits of Models 1 and 2.

Model 3

Model 3 removes the variables that provided insignificant in Model 2, and introduces several dummy variable interactions. These arise from comprehensive testing of the variables from Model 2, across two dimensions of segmentation. The first dimension was road type, as detailed in the preamble to each repetition of the SP questionnaire. This was categorised as ‘urban’, ‘rural’ or ‘motorway’ (with the latter acting as the base). The second dimension was the occupation of the respondent, which was categorised as ‘industrial’, ‘academic’, ‘policy’, or ‘other’ (with the latter again as the base). Only significant interactions are retained.

The first set of interactions, as presented, considers the relationship between occupation and mean speed in excess of the speed limit. Although the dummy variables relating to incremental changes in mean speed continue to support the proposition that excess speed contributes to a reduction in safety, the interactions demonstrate some variation in the perceived relation across occupational categories. From the size and sign of the estimated interaction parameters, one can infer that members of the ‘other’ category show most concern for the effect of excess speed on safety, followed by industry, then academics, with politicians showing least concern of the four categories. Before proceeding, it might also be noted that, in contrast to Model 2, the coefficients on +5% and +10% are no longer significantly different from one another.
Moving on to the speed variation variable, it might be noted that a significant, negative and *common* interaction is estimated for the industry, academic and politician categories, whilst the basic speed variation attribute (i.e. relating to the ‘other’ category) is no longer significant. Thus, respondents from the ‘other’ category perceive no significant relation between speed variation and safety. Respondents from industry, academia and politics, in contrast, perceive speed variation as detrimental to safety, and show agreement on the magnitude of this relation.

Interactions with the variation in lane variable yielded only a single significant parameter, related to medium variation and academic occupation. This result should be taken in partnership with the result that medium variation alone is no longer significantly different from zero. Reconciling these two results, it can be inferred that academics consider medium variation to be less safe than low variation, whilst members of the other occupations categories do not.

Several significant interactions with the minimum headway variable were estimated. Before considering these interactions, it might be noted that the substantive results of the basic minimum headway variables are essentially as Model 2, to the extent that all coefficients remain negative. A notable distinction, however, is that the coefficients on 2 seconds and 4 seconds are no longer significantly different from one another.
Proceeding to the interactions, it is evident that, for urban driving, a minimum headway of 0.5 seconds (i.e. the smallest minimum headway) is considered safer than the same headway on rural roads or motorways. For industry respondents, there is no significant difference, in terms of safety, between minimum headways of 0.5 or 1 second. The same applies to academics. Furthermore, both industry and academic respondents considered the impact of 0.5 and 1 second headways on safety to be of lesser detriment, relative to

respondents from the political and ‘other’ categories. On the contrary, politicians considered a minimum headway of 2 seconds to be more unsafe than respondents from the rest three occupations categories.

Finally, we consider interactions with the awareness attribute. The results for the basic awareness attribute are essentially as before, i.e. all coefficients are positive. As regards the interactions, politicians perceive a significantly stronger relation between awareness and safety than members of the remaining occupational groups. Respondents from industry, in contrast, perceive little difference between ‘fair’ and ‘poor’ awareness, in terms of their effect on safety; the other occupational groups would seem to disagree with this proposition.

A likelihood ratio test revealed that the additional variables of Model 3 together, contribute to a significant improvement in explanatory power over Model 2.

Model 4

As noted above, all the respondents were invited to respond to the 15 repetitions of the SP experiment, and from each repetition, 5 ‘exploded’ choice observations were derived. Such repetition diminishes the informational value of the data, and carries the risk of inducing upward bias in the *t*-ratios. In order to accommodate this possibility, the ‘Jack-knife’ facility offered by ALOGIT was applied to a re-estimation of Model 3. The re-estimation was generated from 20 jack-knife samples, and is presented as Model 4.

Comparing Model 3 with Model 4, it should be noted that several interactions have been removed from the latter; this is because their estimates fell insignificant following jack-knife estimation. More generally, the *t*-ratios of Model 4 show a notable reduction, as compared with those of Model 3. Although our motivation for Model 4 was the potential for bias in *t*-statistics, the jack-knife procedure accommodates a more general range of model mis-specifications. This explains why the jack-knife procedure yields not only different *t*-statistics, but different parameter estimates, as compared with Model 3. Thus, our substantive interpretations - saved for the interactions that are now deemed insignificant - accord with those of Model 3.

4.3.2 Evaluation of variables

Model 4 is preferred, containing correct sign and statistically significant coefficients with appropriate allowance for the multiple response nature of the data. We now provide further interpretation of the results.

The coefficient estimates in isolation have no meaning. They are only of use when taken together and used in ‘forecasting’ the probability that a particular driving scenario is safe or when they are examined in relation to each other, which is the only way in which they can be interpreted.

The speed variation coefficient is -0.0144 for almost everyone (all except the ‘other’ category) and hence makes a sensible ‘numeraire’ in which to express the other values[1].

With regards to **mean speed**, there is little effect of its increase up to 20% above the speed limit. However, moving to a mean speed 50% above the limit from 20% above the limit, has a larger impact than moving from 10% to 20% above. Moving from 20% to 50% is equivalent to 112% speed variation, whilst moving from 10% to 20% above the speed limit is equivalent to 30% speed variation. The speed 50% above the limit compared to

[1] Although values of speed variation in excess of 100% can be implied by this process, which are clearly not sensible, the purpose here is to use the figures as a ‘common currency’ to compare the importance of different attributes.

the speed limit, is equivalent to 178% speed variation. There appears to be some tolerance by respondents for exceeding the speed limit, and it is likely to be a reflection of "normal" driving behaviour. Excessive speed, however, is recognised as unsafe.

The only significant **lane variation** coefficient was high. This has an impact equivalent to 59% speed variation. Thus, respondents believed that some amount of lane variation was acceptable, as long as it was within the boundaries of the lane markings.

There is a strong non-linear effect apparent with respect to **minimum headway**. Moving from 10 seconds minimum headway to either 4 or 2 seconds, corresponds to 23% speed variation. This increases to 94% and 80% for the movement to minimum headways of 1 and 0.5 seconds. Per unit change in seconds, the movement to 0.5 seconds is the largest. For academics, the movement from 2 or 4 seconds minimum headway to 1 second has a lower effect equal to 73% speed variation. This suggests that respondents recognise that headways below 2 seconds are generally unsafe, with very short headways being safety-critical.

Excellent, good and fair **awareness**, relative to poor awareness, are equivalent to 115%, 77% and 57% speed variation. However, for politicians these increase appreciably to 185%, 116% and 96% respectively, suggesting they attribute more importance to this variable.

4.3.3 Forecast analysis

Following the main analysis, the coefficients were used to undertake a forecast analysis. In this exercise, we developed a number of scenarios, each of which described a different type[2] of driver. The standard logit procedure was used to forecast the probability that a scenario was regarded to be safe. The utility of the forecast scenario being safe (U_s) is made up of the driver characteristics, each weighted by their coefficient estimate. The utility of unsafe (U_u) is simply the unsafe constant. These utility were then entered into the logit model to produce a forecast probability (P) as:

$$P = \frac{1}{1 + e^{U_u - U_s}}$$

This provided us with a percentage agreement score, i.e. what percentage of the respondents believed the driver to be a safe one. As road type was found to be non-significant in the previous analysis, the forecast analysis was based on a generic road type. The results are shown in Table 5.

Given the nature of this SP experiment, whereby respondents were required to assess numerous variables simultaneously, we can be comforted by the fact that drivers (a) and (h) were rated as the best and worst respectively. This provides some degree of assurance that respondents were able to complete the exercise to a satisfactory standard.

The forecast analysis is simply a way of being able to rank drivers, given certain combinations of attributes. Only 9.6% of respondents to this survey believe that drivers who talk on their mobile phone while driving are acting in a safe manner, whereas approximately half of the sample believe that exceeding the speed limit by 20% is fine, as long as the rest of their driving is of a high quality (scenario c).

Table 5 Forecast analysis results

[2] These are hypothetical types of drivers and not based on any particular taxonomy

		Generic road		
		Industry	Academic	Policy
a.	Excellent driver – good at everything Driving at the speed limit, speed variation is 0 and low lane variation. Using 2 second headway rule and with excellent awareness.	86.2%	86.2%	94.5%
b.	Avoiding getting caught by the speed cameras Driving at speed limit, 50% speed variation and low lane var. Travelling at 2 second headway with excellent awareness.	75.3%	75.3%	89.2%
c.	"Although I speed, I am a good driver". Driving 20% above speed limit, speed variation is 0 and low lane var. Driving at 1 second headway with excellent awareness.	38.5%	54.1%	62.9%
d.	I'm in an unfamiliar town looking for the right turning Driving 50% under speed limit, 50% speed variation and high lane var. Travelling at 4 second headway with poor awareness.	19.8%	19.8%	19.8%
e.	I'm in a hurry Driving 50% over speed limit, speed variation is 0 and low lane var. Travelling at 1 second headway with excellent awareness.	11.0%	19.0%	25.2%
f.	I'm on the phone! Driving 20% below speed limit, 50% speed variation and high lane var. Driving at 2 sec headway with poor awareness	9.6%	9.6%	9.6%
g.	Aggressive driver Driving 20% above speed limit, 50% speed variation and high lane var. Driving at 0.5 second headway with poor awareness	0.8%	1.4%	0.8%
h.	Bad driver, poor at everything Driving 50% over speed limit, 50% speed variation and high lane var. Travelling at 0.5 second headway with poor awareness.	0.2%	0.3%	0.2%

4.4 Conclusions

This exercise involved a novel application of SP to quantify experts' attitudes to driver safety and the key factors which impact on it. We are not aware that such an investigation has been previously attempted. We have been able to estimate models where the main effects are statistically significant, correct sign and generally plausible in magnitude. The results imply that there will be considerable differences in driver safety across different contexts that can be described by the five attributes covered in this study. However, there is not a great difference in opinions between politicians, academics and those working in industry, as to what is and is not safe driving and the type of road had a negligible influence.

5 Evaluating a methodological paradigm for the estimation of accident risk probability

5.1 Introduction

In the driving context, a vast number of behavioural parameters have been identified as contributing factors to accident risk. In an attempt to categorise them, speed could be considered as the central parameter, such that it represents the cumulative effect of several and various factors, either set by the internal goals (e.g. driver's state, motives, attitudes to risk, driver's anticipations/ expectations) or by the behaviour of vehicles (traffic flow, vehicle type), hazards (type of road, other road users, road/ weather condition, time of day) or traffic control signals in front. Speed seriously affects the likelihood of a driver being involved in a potentially hazardous situation, as well as the possible corrective action for collision avoidance. As Evans (1991) suggests, high vehicle speed quadruples the threat to driver safety, in the sense that: (a) it increases the likelihood of loss of control, (b) it decreases the probability that a hazard will be detected in time, (c) it increases the distance travelled before a successful avoidance manoeuvre can be implemented, and (d) it increases the damage on impact.

However, driving speed alone, cannot be used as a valuable index for predicting accident risk. Analysis of accidents shows that speed in some way or another plays a part in the cause of many accidents, but accidents are not evenly distributed over road and traffic types. More importantly, accident data (from the AIDE workshop in Munich) indicate that most accidents take place under theoretically optimum traffic/environmental conditions, namely, in non-clustered environments (rural roads), with good road surfaces (dry road), with no other road users (single-driver accidents), rather than under theoretically more dangerous traffic/environmental conditions, namely, in clustered environments (e.g. urban roads) or traffic environments where vehicles are travelling at higher speeds (e.g. motorways), under heavy traffic flow and/or bad road surfaces (e.g. wet roads).

At first glance, this contradictory finding seems to be in accordance with the risk homeostasis theory (Wilde, 1982; 1988), stating that drivers adjust their behaviour so as to maintain the level of accident risk at some subjectively acceptable, target level. That is to say, safer traffic/ environmental conditions favour driving at higher speeds that, in turn, increase the likelihood of loss of control. This behavioural adjustment is the result of drivers' attempts to maintain the same level of accident risk, both in theoretically safe and theoretically dangerous traffic situations. But since there is no direct way to measure the desired or target level of risk, this theory ends up being circular.

Instead, a more pragmatic view for understanding a complex task like driving, is Rasmussen's (1982) three-level taxonomy of human performance control, namely: the knowledge-based level, the rule-based level and the skill-based level. At the heart of this model (Hoedemaeker, 1999), lies the idea that as long as discrepancies between the actual and the desired state of the system (in this case, the vehicle and the environment) are not very high, human performance is carried out at the lowest, skill-based level, implying that task performance takes place in open-loop control, i.e. without continuous monitoring of feedback. Only if something goes wrong in this open-loop mode, does this trigger task performance to be carried out at a higher level, namely at rule-based level, where human behaviour is controlled by a set of rules that have proven to be successful previously. Task performance mostly takes place in close-loop control, or at knowledge-based level, requiring much more attention and effort than the lower two levels.

In respect to the accident statistic data mentioned above, it is interesting to note that Rasmussen's taxonomy provides a better insight regarding the accident distribution in the theoretically safer and theoretically more dangerous traffic/environmental conditions, in the sense that a single-driver accident in a non-clustered environment is more likely to happen, not necessarily because drivers are underestimating the risks, but simply because drivers do not notice (e.g. from traffic environment cues), in time, that something is amiss in the open-loop mode, and thus, they continue driving at skill-based level, as they do in normal circumstances. The basic difference with risk homeostasis is that accident risk is not realised as a function of accepting a higher level of risk, in general, but as a function of failure detection of situation demands on time (Rumar, 1990), and consequently, as a function of putting less attention and effort in monitoring of task performance and action consequences.

If this is the case, then accident risk probability is related to the timing of hazard detection, that it is reflected through time delays in triggering adjusting activations to perform tasks at the higher level (i.e. timely detection of deceleration of the lead car; faster reactions to unexpected decelerations in car-following situation; faster reaction to unexpected behaviours in cross-sections). Alternatively, if situational demands are very high and task performance is carried out at higher level, then accident probability is related to the side-effects of increasing effort and workload, but the accident risk is actually lower because drivers are ready to confront unexpected events.

To create these conditions in a driving simulator environment, we used the paradigm of fixed time schedule, described in van der Hulst, Rothengatter and Meijman (1999). According to this paradigm, two groups of participants are used. In the control group, participants are instructed to drive a 14-minute journey, as they would normally do. In the experimental group, participants are instructed to complete the same journey in less time, in 12 minutes. To ensure that participants in the experimental group are in compliance with the fixed time schedule, feedback messages are projected on the simulator screen in order to inform them whether they drive on or behind schedule.

The fixed time schedule is expected to trigger participants to perform at higher level, namely, at the rule-based level (refers to how drivers attend and perceive information from the traffic environment) and/ or at knowledge-based level (refers to drivers' attention and also effort to control the vehicle at high speeds). On the other hand, the free-driving condition is expected to trigger participants to perform at lower level, namely at the skill-based level. The aim of the study presented in this document is to investigate: (a) whether a fixed-time schedule paradigm can be used as an extended methodological paradigm to estimate accident risk probabilities both in longitudinal and lateral behaviour, and if so, to further investigate (b) whether, the temporal adjustment activations in task performance that, according to Rasmussen's taxonomy, are triggered from situational demands, should be taken into account in testing the risk probability related with ADAS use.

5.2 Method

5.2.1 Participants

20 participants, 10 male and 10 female, were allocated to two groups: the control group and the experimental one. Participants were between 23 and 45 years old with a mean age of 32 years. They held a driving license for 3 to 24 years (mean=12.2 years). Their previous year's mileage ranged between 5000 to 60000 km (mean=28683.3).

5.2.2 Apparatus

The experiment was performed on the HIT driving simulator which is built around a Smart cabin equipped with sensors, Figure 4. The position of all control levers, windshield wipers, indicators, ignition key and light switch is recorded. All operational elements, steering wheel, accelerator pedal, brake pedal, gearshift lever and handbrake lever, provide natural force reactions. The gearshift functions like in the real car either as automatic or "softtip" with incrementing and decrementing the six gears and with reverse gear.

The projection system includes five large-screens, each having a width of 2 m. There is on-screen projection with consumer video projectors with 2500 ANSI-lumen. The sound system generates original sounds according to the situation (starter, engine noise, horn, screeching of tires, wind, rain, etc.). The vibration device creates nature true vibrations of the car according to the revs of the simulated engine.

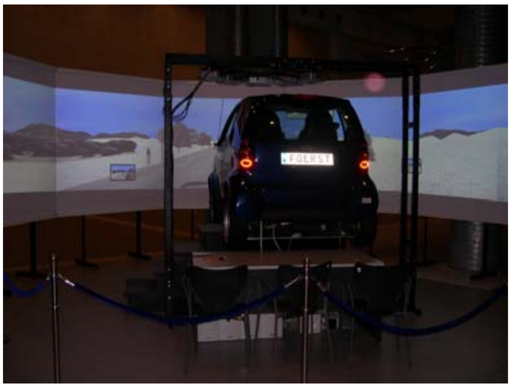

Figure 4 View of the HIT driving simulator (left) and driver's field of view (right)

5.2.3 Experimental design

The experiment took place using a circular route, total length 6.2 km. This route is mainly a rural route, one lane in each direction, no central border. For approximately 500 m this route passes through an urban area. There are 2 signalised intersections and 1 non-signalised intersection along the route. The scenario implemented for this experiment included two continuous and uninterrupted drives of the circuit. There were oncoming vehicles and vehicles in front of the driver. Some of them were driving at low speed. Overtaking in general was possible in the rural part, but risky.

During the first drive, the driving behaviour of the other road users was in compliance with traffic rules and no other unexpected traffic events took place. During the second drive, the following unexpected traffic events/scenarios occurred:

- Sudden deceleration of the lead vehicle (twice);
- Animal crossing;
- Parked car suddenly entering into the lane in front of the driver;
- Parked car suddenly opened a door in front of the driver.

All these events were distributed within the second drive in such way, so that in the meanwhile, participants were confronted with correspondent traffic events/ situations, without being at risk. This situation might progressively has triggered adjustment activations, especially in control group, so that task performance would be carried out at skill-based level. Instead, in the control group the fixed time schedule should minimise such possibility.

5.2.4 Procedure

Upon arrival, subjects were asked some personal data questions, like age and driving experience. Then, they were asked to drive for 5 minutes in the driving simulator, in order to become familiarised with it. Then, the actual experiment was conducted, with the subjects driving the two drives continuously and without interruption.

5.2.5 Measures and analysis method

The driving behavioural parameters that were continuously recorded are:

- Time,
- number of accidents,
- vehicle speed,
- distance to lead car,
- time when the subject started braking or initiated an evasive manoeuvre in relation to a critical event.

An evasive manoeuvre was defined as a sudden change in the steering angle, resulting in a change in the simulator vehicle lateral position towards the right of the road.

The following indicators were calculated:

- Response time to a critical event. This was the time that the subject initiated a braking action or an evasive manoeuvre in relation to a critical event.
- Headway to lead car at the moment when the subject started braking or initiated the evasive manoeuvre.
- Minimum headway during following, defined as minimum headway from the moment when the subject started braking or initiated the evasive manoeuvre until the simulator vehicle has crossed the lane border towards the adjacent lane.

The effect of time pressure on the behavioural variables was analysed with analysis of variance.

5.3 Results

5.3.1 Vehicle speed

There was a significant difference in mean vehicle speed between the No pressure and Time pressure groups for the first drive ($p>.05$) and a trend for the second drive with the unexpected events ($p=.06$), see Figure 5.

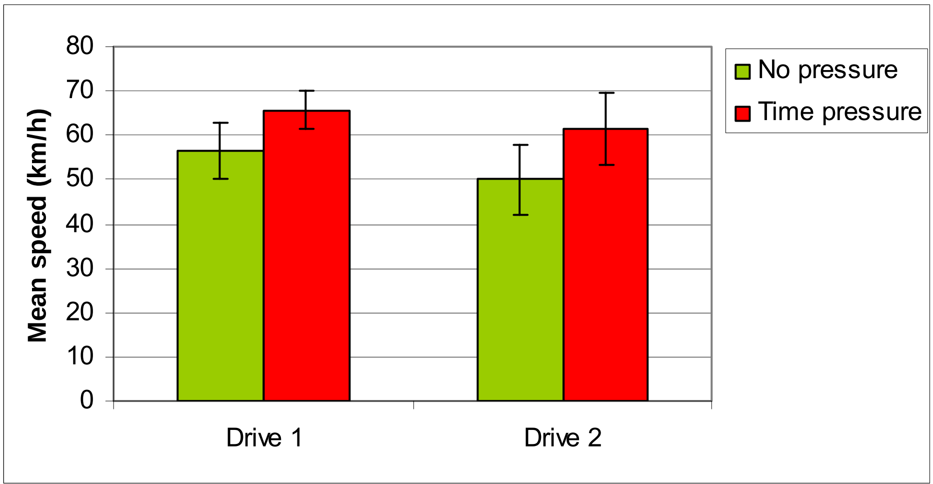

Figure 5 Mean speed

Drivers under time pressure drove faster, by approximately 10 km/h. There were no significant differences between the two drives, and no interaction was found.

5.3.2 Number of accidents

The total number of accidents was found to be higher in the Time pressure group than in the No pressure group (ten and six accidents, respectively), as shown in Table 6. However, looking at the distribution of the accidents through the entire driving route, as well as the type of accidents, there is a clear distinction between the two groups in relation to drivers' alertness to unexpected traffic events. Specifically, in the No pressure condition, 5 out of 6 accidents were related to drivers' inability to avoid an unexpected traffic event, whereas, only one accident was related to loss of vehicle control; and this took place within the second drive. Instead, in the Time pressure condition, 3 out of 10 accidents were related to loss of vehicle control (both in the first and the second drive), whereas, all the rest of the accidents occurred when the animal entered the driver's path.

Table 6 Total number of accidents

Driving Route	Accident type	Number of accidents	
		No pressure	Time pressure
Drive 1	Road exit		2
Drive 2	Animal	3	7
	2nd lead vehicle braking	1	
	Car park	1	
	Road exit	1	1
	Total	**6**	**10**

On the other hand, considering that in the Time pressure condition the mean speed was much higher than in the No pressure condition (about 10 km/h), in addition to response time to unexpected events (see Figure 6), being generally lower in relation to the No pressure condition, this type of accident is more representative of drivers' inability to adequately stop the vehicle when travelling at such speed, rather than drivers being not prepared enough to react to a sudden traffic event.

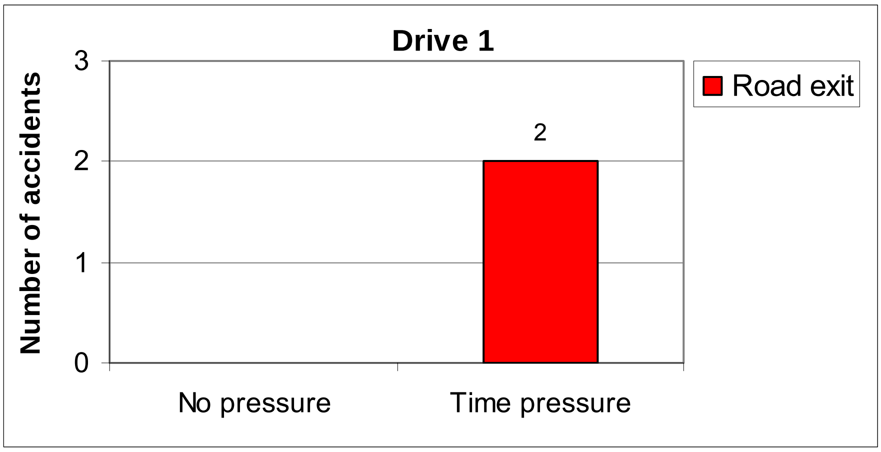

Figure 6 Number of accidents (Drive 1)

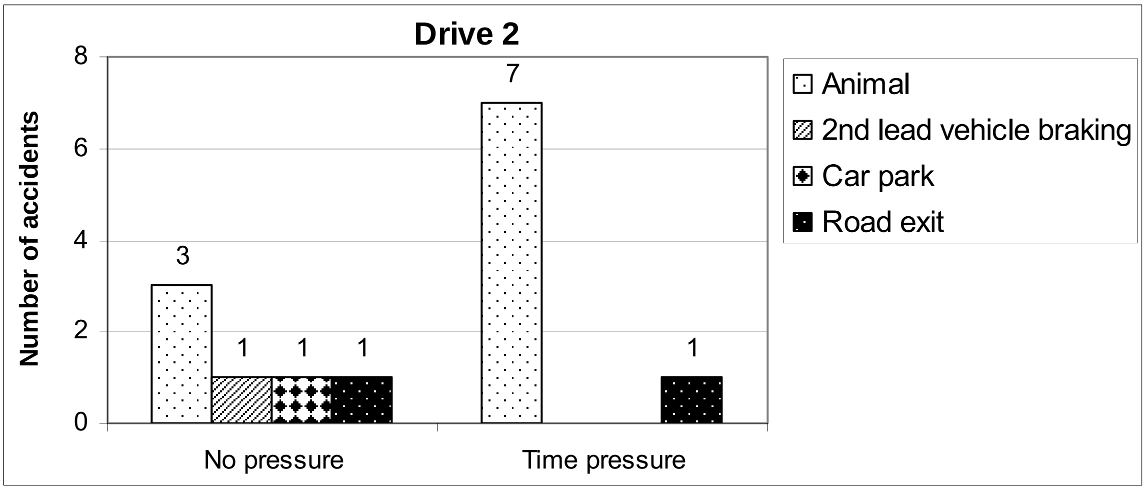

Figure 7 Number of accidents (Drive 2)

Therefore, it could be concluded that time pressure had a positive effect in relation to drivers' alertness to react or even to foresee an unexpected traffic event, but this was accompanied by a higher number of accidents, mainly related to loss of vehicle control (due to higher speed).

5.3.3 Response time to a critical event

The response time has been calculated as the time the subject initiated a braking or evasive manoeuvre in response to one of the critical events, minus the time that the critical event was initiated. It could be the case that this manoeuvre was initiated a bit before the critical event initiation, because the subject had anticipated the possible critical event. Therefore, the response time to a critical event is generally lower in the Time pressure group and the difference is significant in the lead vehicle braking and door open cases, see Table 7.

It is interesting to notice that (a) the two brake events can be considered as comparable to one another, in terms of time adequacy for foreseeing driver behaviour of the vehicle ahead in the near future, (b) the parked car and door open events can be considered as comparable to each other, in the sense that they both represent hidden traffic dangers which could occur in an urban environment, whereas, (c) the animal entrance event is quite different in the sense that it represents a stochastic traffic danger which occurs suddenly as the target vehicle approaches it.

With this in mind, it is worth noting that during the first case of braking, participants in the Time pressure group had already decided to overtake the lead vehicle, even before it braked, whereas participants in the No pressure group continued car-following and responded to sudden braking considerably later. This implies that, at that moment, the two groups had a different "strategy" in managing traffic conflicts, which does possibly reflect the additive effect of different time constraints and the normality of traffic events within the first drive. Instead, during the second case of braking, participants' performance, especially in the time-pressure group, was not as expected, in terms of response time and time-headway.

To understand this result, we have to take into account the possible side-effects of the sequence of the traffic events within the first drive. Specifically, after the first lead vehicle suddenly braked, both groups started to progressively increase time headways at which they started their reaction (Figure 9), which implies that the first unexpected event resulted in increased safety margins for both groups (Brown, 1990). This was as a consequence of drivers' awareness that traffic danger could occur rather than as a consequence of the normality of traffic in the first drive. Following this line of reasoning, the results suggest that after the first event, participants in the Time pressure condition adjusted their driving performance by keeping the minimum possible safe distances (knowing that they were driving into a dangerous traffic environment) and responding to dangers as fast as possible (considering time adequacy for responding or foreseeing each type of danger). On the other hand, participants in the No pressure condition adjusted their performance by keeping longer distances and responding to dangers considerably slower in comparison. These differences between the two groups are difficult to be attributed to the previous experience of participants within the first drive. A more plausible explanation seems to be that the unexpected event simply "cancelled" the effect of traffic normality in the first drive, and differences in response time(s) between the two groups are more representative of participants' attempt to minimise the effort by driving more conservatively in the No pressure condition. Accordingly, participants attempted to minimise the possibility of having an accident by driving more "carefully" in the Time pressure group.

Table 7 Response times

Response time (s)	No pressure	Time pressure	Significance
1st lead vehicle brake	4.36	-0.15	p=0.00204
Animal	1.93	1.57	No
2nd lead vehicle brake	5.90	1.67	p=0.0222
Parked car entrance	0.82	-0.03	No
Door open	4.18	-0.71	p=0.0198

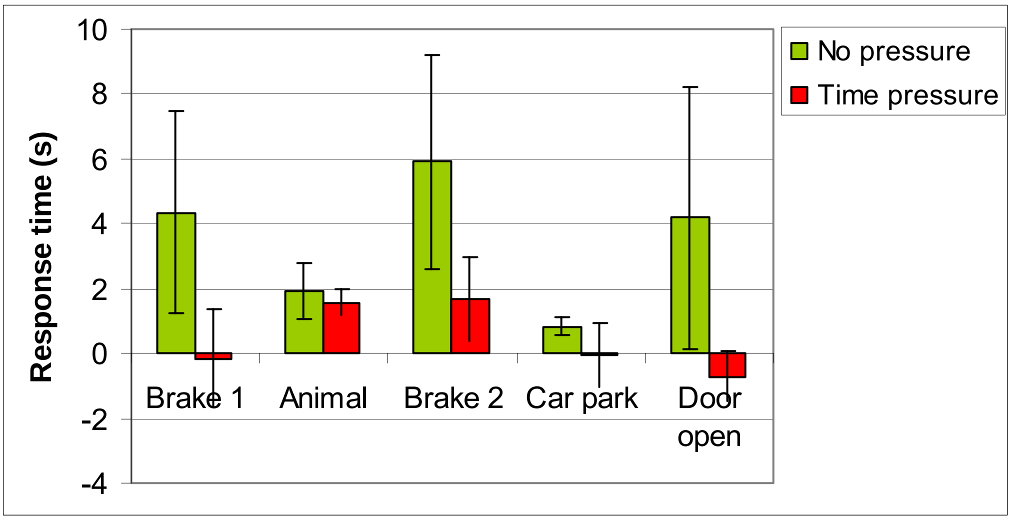

Figure 8 Response times

5.3.4 Headways

There was a difference in the headway at which the subject initiated the evasive manoeuvre, or started braking when the lead vehicle braked, or the animal entered the driver's path. In the Time pressure group, the headway was consistently shorter, but only significantly in the case of the second lead vehicle braking (p>.05); see Figure 9.

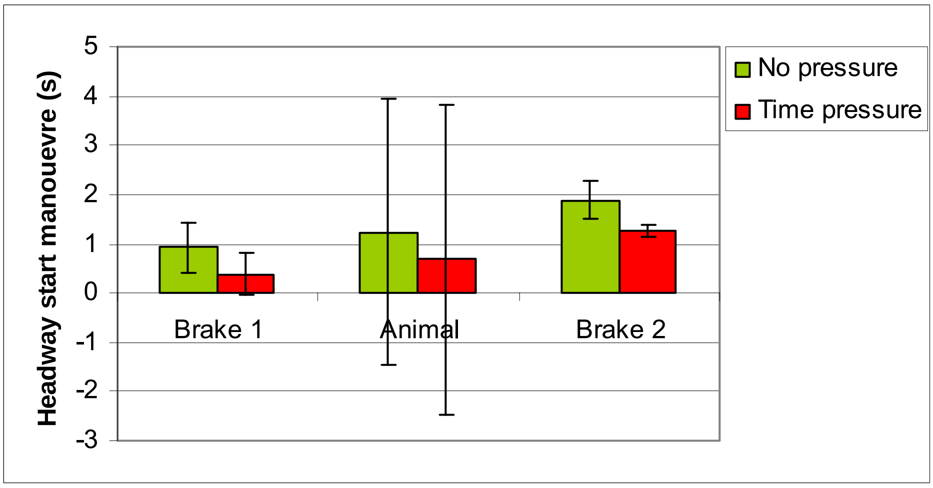

Figure 9 Headway at the start of the evasive manoeuvre

The minimum headway from the moment when the subject started braking or initiated the evasive manoeuvre until the vehicle has crossed the lane border towards the adjacent lane, are shown below. There were no differences between the groups.

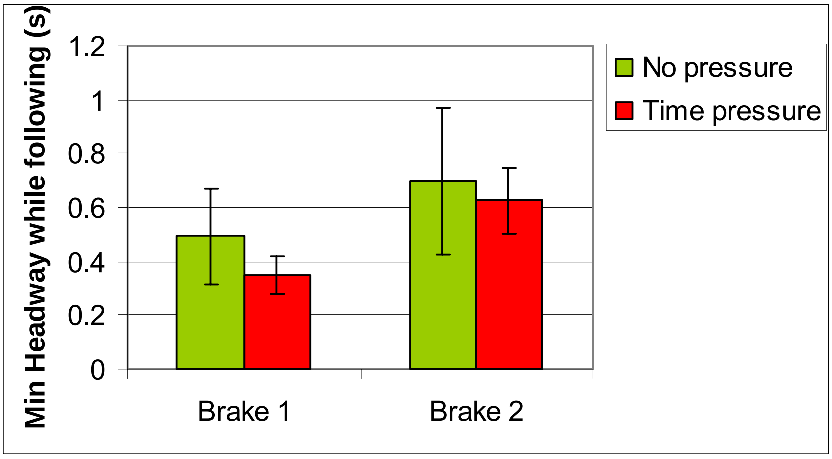

Figure 10 Minimum headway while following

5.3.5 Lateral position

Finally, there were no significant differences between the groups regarding lateral position in the No pressure and Time pressure groups, as shown in Figure 11.

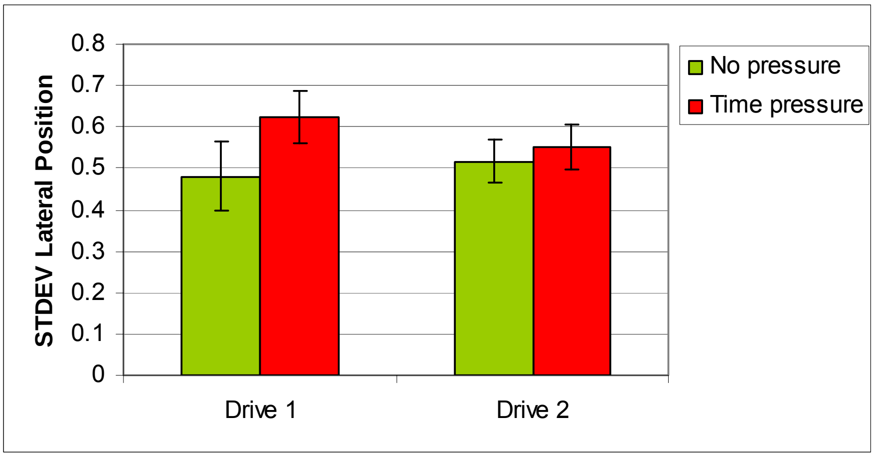

Figure 11 Standard deviation of lateral position

5.4 Conclusions

The authors hypothesised that time-pressure would trigger participants to carry out their performance at a higher level and thus, lower their accident risk probability compared to a no-pressure condition. There were two types of analyses carried out: first, whether the fixed-time schedule paradigm had an effect on the number of accidents and second, whether the normality of traffic events within the first drive had a different effect on participants' alertness in reacting to unexpected events throughout the second drive.

Regarding the first issue, time pressure did have a significant effect on mean vehicle speed, as expected, but the number of accidents was much higher in the Time pressure group than in the No pressure group. In the No pressure group, almost all accidents were related to the unexpected traffic events; instead, in the Time pressure group, nearly all accidents were related to loss of vehicle control. In other words, time pressure had a positive effect in relation to drivers' alertness to react or even to foresee an unexpected traffic event, but this was offset by a higher number of accidents either related to increasing effort, or related to drivers' skills in maintaining vehicle control at higher speeds.

Regarding the second issue, traffic normality within the first drive did have a significant effect on participants' response times to the sudden braking of the lead vehicle, but not on animal crossing and parked car entrance. As already discussed, this result should be understood as a side-effect of the sequence order of traffic events, in the sense that animal entrance, which represents a more stochastic traffic danger, increased participants' awareness that any traffic danger could occur, irrespective of their previous experience within the first drive. This is particularly evident by the increasing time headways in both groups, as the number of unexpected events was also increased. Following Rasmussen's terminology, this finding implies that after animal entrance, both groups were triggered to perform at a higher level, namely at rule-based level. However, considering response times to unexpected events, the main difference between the two groups, is that participants in the Time pressure condition adjusted their performance by keeping minimum safe distances and reacting or foreseeing to imminent or hidden dangers as fast as possible. On the other hand, participants in the No pressure condition adjusted their performance by keeping longer distances and reacting considerably slower in comparison to the other group. If this holds true, then the strategy followed by the No pressure group could be interpreted as an attempt to minimise discrepancies between the actual and the desired state of the system vehicle-environment, permitting them to perform at the lowest, skill-based level. Conversely, the strategy followed by the Time pressure group could be interpreted as an attempt to balance the discrepancies between the actual and the desired state of the system vehicle-environment performing at rule-based level, but at the cost of increased effort.

As a general conclusion, the fixed-schedule paradigm can be considered as an appropriate methodological paradigm for studying driving behaviour under conditions of drivers' full alertness, but in relation to the estimation of accident risk probability more issues need to be clarified. Specifically, the fact that in the Time pressure condition the majority of accidents were related to loss of vehicle control and not to drivers' ill-preparedness in reacting to unexpected events, is difficult to be attributed, on the basis of these results, as a sole result of drivers' inability to maintain vehicle control at high speed or simply as a result of drivers' increasing workload and/or effort. This issue has important implications in estimating accident risk probability related to ADAS use, since in the former case ADAS use might have a positive effect in relation to vehicle control, whereas, in the latter case, ADAS use might have a negative effect by increasing drivers' workload. Thus, further research is needed in order to clarify what is the effect of increased workload on drivers' performance in time-pressure and no-pressure conditions.

6 The potential of using micro-simulation in traffic risk estimation

6.1 Objectives

The premise for the work presented in this section is that any risk assessment requires a model of the risks in question. In the case of AIDE, this means a risk model that can be used to identify – and predict – the risks emanating from various ADAS, IVIS and nomad systems, as well as from the integration itself.

Such a risk model must comprise the overall driving task (i.e. navigating safely through the traffic), and the ways in which various technologies may affect that. Since the precise nature of the technologies to be considered is unknown at present, it is proposed that the risk model considers a critical aspect of driving, such as maintaining longitudinal separation (other possibilities would be lateral separation, longitudinal and/or lateral position, speed, etc.)

A risk model describing the impact of ADAS relating to longitudinal separation was developed in this study. This risk model is expressed as an event tree, which comprises the various technological and driver actions that together constitute safe driving. After the risk model had been developed, a micro-simulation model was used to quantify the risk of the system, and to provide an integrated simulation of how an AIDE system might function.

In addition to developing event-tree based risk models for specific ADAS functionalities, it should also be considered to develop a more comprehensive fault-tree based risk model for an AIDE system as such. The two types of modeling would obviously complement each other, and benefit from the use of existing driver models as well as empirical data of specific phenomena such as drowsiness, workload, inattention, etc.

The objective of this study is to develop a risk estimation method which integrates static system analysis techniques and a micro-simulation model. In system safety, static analysis techniques, such as event and fault trees, have proved to be useful tools for studying the possible outcomes of a given initiating event and probable contributing factors of a selected undesired event. While the static analysis techniques assume that the sequence of events and their interactions are fixed, it is not true in many systems as well as in driving. Driving is never a sequence of predefined tasks. In contrast, it involves dynamic environment and interactions between road users. In order to take the dynamic and interactive characteristics of driving into account, the risk assessment method takes advantage of a micro-simulation model, which is able to create a dynamic and interactive world.

6.2 Methodology

In this section, two system safety analysis techniques and the reasons for using a micro-simulation model are presented.

6.2.1 Event tree analysis

Binary logic is the basis of event tree analysis. Whether an event has or has not happened, or whether a component has or has not failed, is being represented in a binary branching tree. Event tree analysis is valuable in analyzing the consequence arising from undesired events or component failures.

An event tree begins with an initiating event, such as approaching a sharp curve or an insufficient longitudinal separation. The consequences of the initiating event are followed through a series of possible paths. Each path is assigned a probability of occurrence and then the probability of the various possible outcomes can be calculated.

6.2.2 Fault tree analysis

Fault tree analysis provides a systematic description of the combinations of possible occurrences in a system, which can result in an undesirable outcome.

A fault tree begins with a Top Event, which is the most serious outcome, such as collision, injury or fatality. A fault tree is then constructed by relating the sequences of events, which individually or in combination, could lead to the Top Event. This may be illustrated by considering the probability of events and constructing a tree with AND and OR logic gates. The tree is constructed by deriving in turn the preconditions for the top event and then successively for the next levels of events, until the basic events are reached.

6.2.3 Micro-simulation model

Active safety measures, e.g. ADAS, aiming at preventing driver erroneous actions, have become dominating in road safety. This requires a generic, industrially applicable, methodology for the evaluation of active safety measures with respect to safety. The prerequisite of such methodology should be able to address the effects of driver behaviour and road-user interactions. Micro-simulation has proved to be a useful tool for studying the traffic system, where the behaviour of the system is largely dependent on the behaviours and interactions of road users (Archer & Kosonen, 2000). Although micro-simulation has been applied mainly in road design and traffic control studies, it has a promising potential in the evaluation of the safety impact.

6.3 Results

One of the goals in SP2 is to assess the risk reduction of integrated ADAS. For such purpose, two ADAS applications, Adaptive Cruise Control (ACC) and Collision Warning and Avoidance (CWA), were selected from the inventory of longitudinal control ADAS applications in AIDE Deliverable 2.1.2. In this section, the results of event tree based and fault tree based risk models are presented. Since the experiment of micro-simulation is planned to be completed in AIDE working package 2.3.3, only the concept linking an event tree based risk model and a micro-simulation model is presented in this section. For more details and results of the experiment, please refer to AIDE Deliverable 2.3.3.

6.3.1 Event tree based risk model

Two event tree risk models are produced in this study. One risk model describes possible consequences of an initiating event for a vehicle without ADAS. Another model also describes possible consequences of the same initiating event but for a vehicle with ADAS.

The initiating event of the analysis is when the longitudinal distance between two cars is reducing. This reducing gap might due to the sudden speed reduction of the leading car, a car approaching with a speed higher than the leading car, or other reasons. Once the separation is small than an extent, a host of events will follow.

Figure 12 shows the possible consequences of the initiating event for a vehicle without ADAS. The driver is the one who should notice the short distance and takes responding actions, e.g. braking. If both are done properly, as the upper path (path #1) shown in

Figure 12, no collision will occur. If the driver fails to detect the critical distance or fails to respond to the situation properly, a collision will occur.

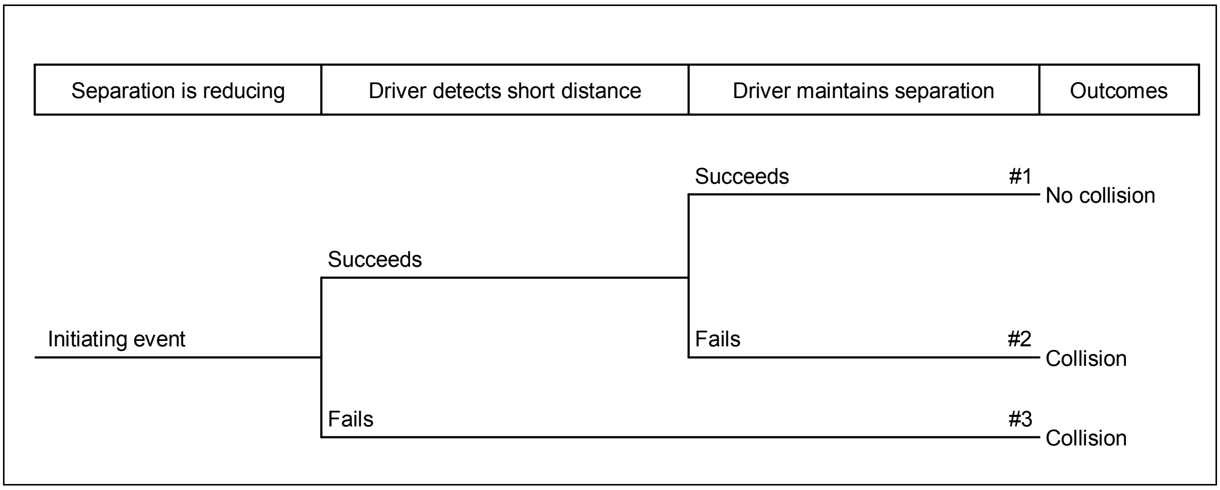

Figure 12 Event tree for vehicle not equipped with ADAS

The probable outcomes of vehicles equipped with ADAS are much complex than the probable outcomes of not equipped vehicles. Before jumping into the analysis, the functions of ACC and CWA are briefly presented.

A car with ACC can cruise either at the speed set by the driver or at the speed of a leading car, according to situations. In the latter case, the two cars will maintain a gap which is set by the following car, e.g. 3 second distance.

CWA is a system which can detect vehicles or obstacles ahead. CWA firstly issue warning messages to drivers when an obstacle is detected. And an automatic braking will intervene in case the drivers fail to react.

The initiating event, as same as vehicle not equipped with ADAS, is that the distance between two vehicles is reducing. The ACC will maintain a predefined time distance when the speed of leading vehicle is slower than its predefined cruise speed. So the ADAS equipped vehicle should maintain the predefined time distance when the gap is smaller than it. As a consequence, there is no collision (the upper branch at the event of *ACC maintains separation* or path #4 in Figure 13). Since the ACC operates as it should be, there is no need for further analysis in this branch. However, the ACC may not be able to maintain the predefined distance (the lower branch at the same event). The possible reasons for the malfunction of ACC can be found in the fault tree based risk model, described in the next section.

The further reducing distance can be stopped by the driver if s/he detects it. This driver preventive action contains two events: *Driver detects a short distance* and *driver maintains a distance.* If a driver successfully detects a short distance and maintains a gap, no collision will occur (path #5). If a driver detects a short distance but fails to maintain a gap, e.g. panic, a collision can be avoided if CWA stops the car (path #6), or will occur if the CWA fails to stop the car (path #7).

In the lower branch of the event, the *driver detects a short distance*, and there are four events relating with the CWA and the driver. The first event is whether the CWA succeeds in issuing warning messages to a driver. The second and third events are whether a driver succeeds in receiving warning messages and maintaining a gap. The fourth event is whether the CWA succeeds in stopping the vehicle. The analyses of these events are similar with the analyses of the ACC and driver events above, and their results are shown in Figure 13. Path #8 represents warning messages that are issued and received by the driver and then the driver take proper actions to maintain a separation. A collision is successfully prevented by the CWA (path #9, #11 and #13). A collision occurs due to the failure of the CWA and other previous events (path #10, #12 and #14).

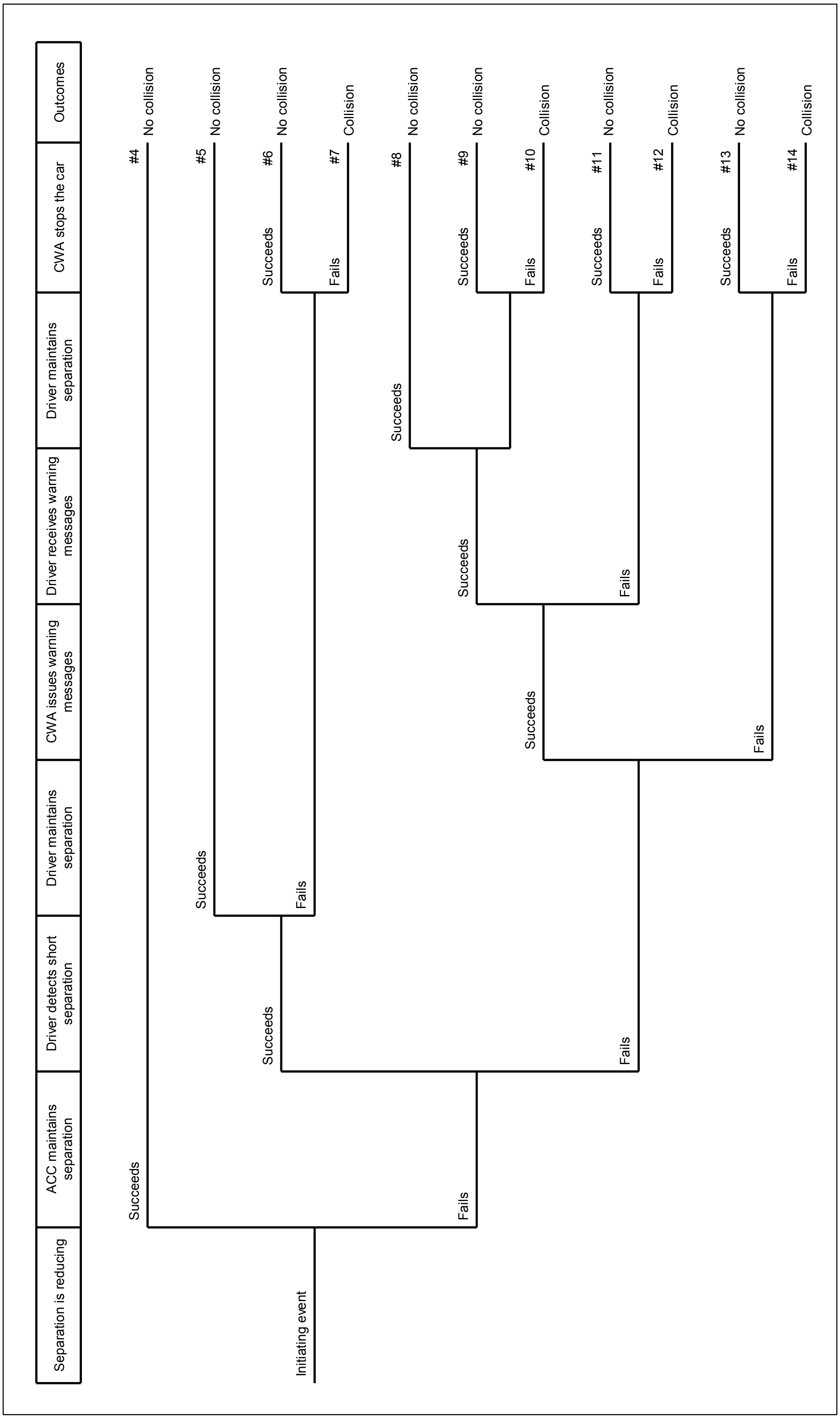

Figure 13 Event tree for vehicle equipped with ADAS

6.3.2 Fault tree based risk model

The Event tree analysis is a forward analysis technique. It helps to predict possible consequences according to given conditions, but does not provide the reasons for the occurrence of the conditions. Fault tree analysis provides a systematic description of the combinations of possible occurrences in a system, which can result in an undesirable outcome. Hence, the fault tree analysis can complement the shortage of event tree analysis.

A fault tree risk model was produced in this study (Figure 14). An ACC and CWA equipped vehicle which has a collision with an object ahead was analyzed. A collision with object in the front is selected as Top Event. The occurrence of the top event concerns with three events below it. Only when the three events are true, will the top event be true, i.e. a collision occurs. The three events are when the ACC fails to maintain a separation, a driver fails to maintain a separation and the CWA fails to stop the vehicle.

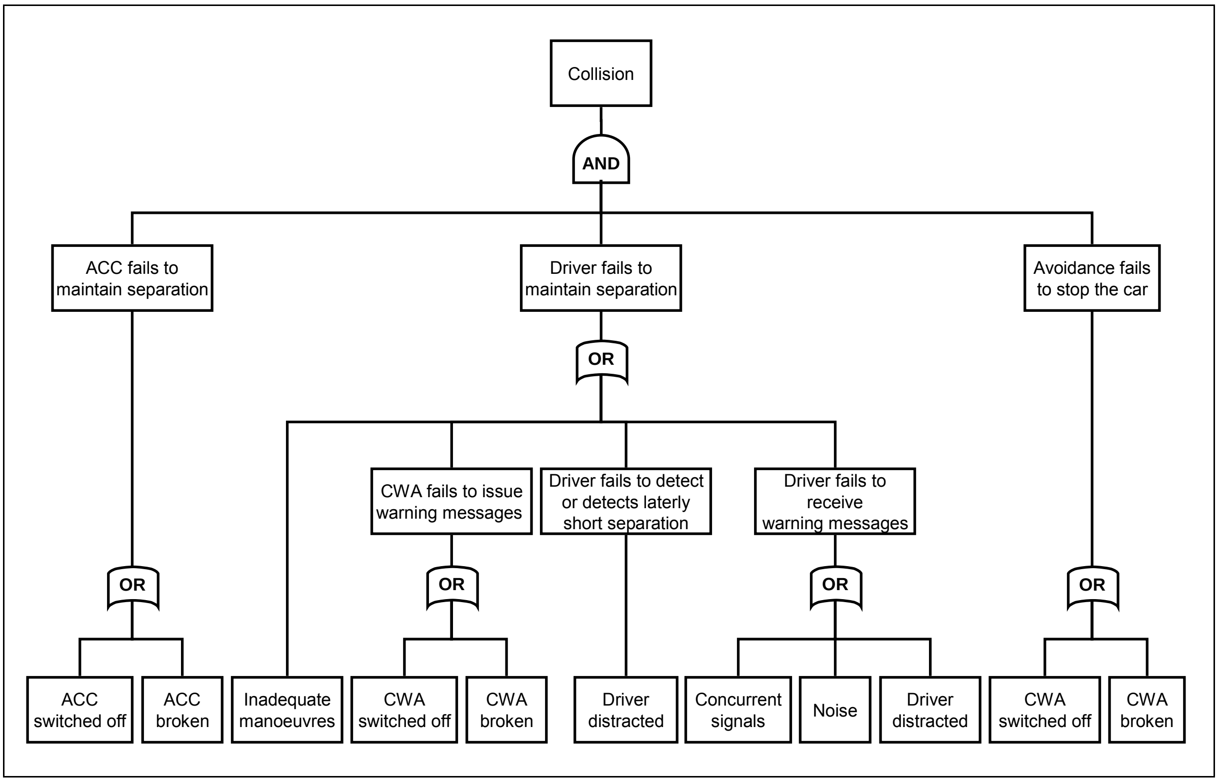

Figure 14 Fault tree for vehicle equipped with ADAS

The reasons for the failures of the ACC, the driver and the CWA are analyzed. The ACC fails to maintain a separation because it is broken *or* has been switched off. Either broken or switch off can fail the intended ACC's function. Analysis can be continued on both events if further analysis is needed and related information is available. The analysis of the ACC branch stops here because the lack of information. Hence, *ACC being switched off* and *ACC is broken* are basic events. The same procedure can be applied on the analysis of Driver and CWA branches. So the details of the analysis of the two branches are skipped here.

6.3.3 Micro-simulation

A micro-simulation model is used in this experiment. The model is extended from the RuTSim, so driver behaviours and road-user interaction can be simulated. The main difference between RuTSim and the extended RuTSim is that the latter has a car-following model with a flexible acceleration function, explicit time modelling and a desired following distance. For further detail about the extended RuTSim model, please refer to Chapter 4.

Vehicular behaviour is the basic simulation element in the extended RuTSim. In order to simulate the various behaviours of ADAS equipped vehicle, two parameters (acceleration and reaction time) in the car-following model are manipulated by referring to the event tree model (Figure 13). Acceleration is defined as the average accelerating rate of the decelerating process, which starts when the first action is taken and ends when a desired following distance is reached. The values of acceleration in Table 8 are negative, because vehicles decelerate to avoid a collision. Reaction time is defined as the difference between the time when an action should be taken and the time the first action is applied. For instance, to simulate a vehicular behaviour in which ACC succeeds in maintaining a separation (path #4 in Figure 13), the two parameters are set as: lowest deceleration (-a1) and shortest reaction time (r1) (Table 8). In the case a collision is prevented by the CWA (path #6, #9, #11 and #13), the parameters have highest deceleration (-a5) and longest reaction time (r5). Although path #6 might slightly different with the other paths (the driver is aware of a short gap in path #6 but not in the others), here they are assumed to be same.

Brookhuis and de Ward (2004) points out that the drivers driving ADAS equipped cars have a longer reaction time compared to drivers driving normal cars. Hence, drivers that succeed in detecting a short gap and maintaining a safe separation in a vehicle equipped with no ADAS (path #1 in Figure 12), have shorter reaction time than in a vehicle equipped with ADAS (path #5 in Figure 13). Path #8 has a longer reaction time than path #5, because the drivers fail to detect a short gap in the former.

In case a collision occurs (path #2, #3, #7, #10, #12 and #14), the drivers have no or near zero deceleration and very long reaction time.

The desired following distance depends on the distance maintained by the ACC, the CWA or the drivers themselves. The distance maintained by the ACC (path #4) is shorter than the one maintained by a driver (path #1, #5 and #8). The distance is shortest when a vehicle is stopped by the CWA (path #6, #9, #11 and #13). The setting of all parameters for various vehicular behaviours is shown in Table 8.

Table 8 Parameters for different vehicular behaviours

Path	Acceleration	Reaction time	Following distance
#4	-a1 (Lowest)	r1 (Shortest)	d2
#1	-a2	r2	d3 (Longest)
#5	-a3	r3	
#8	-a4	r4	
#6, #9, #11, #13	-a5 (Highest)	r5 (Longest)	d1 (Shortest)
#2, #3, #7, #10, #12, #14	~0	∞	~0

The scenario of the experiment is based on a 8 km long two-lane rural road, located in the southern part of Sweden. It consists of six intersections. Traffic volumes correspond to the average hour in 2004 and traffic flows contain cars and trucks with and without trailer. The truck percentage of the traffic is approximately 15%.

Accident risk is assessed by referring to the number of critical event. A critical event is an event in which the time-to-collision (TTC) of a following vehicle is less than a threshold.

The threshold is selected according to the breaking capability of the CWA. It means, whenever the TTC is less than the threshold, a collision is unavoidable.

6.4 Conclusions

The two event trees presented in Figure 12 and Figure 13 can be further developed if the detailed sequences of specific event are needed. For instance, the maintenance of time distance of ACC can be divided into detection and action steps, and whether or not an activities is concurrently performed when drivers is receiving a warning signal can be considered. The analysis of more specific events will help to single out more specific causes that affect the risk of an accident. However, the failure rate of specific events is usually not covered in historical data and need to be assessed.

The fault tree risk models (Figure 14) show the drivers of ADAS equipped vehicles to still play a critical role in the goal of safe operation. Collisions are likely to occur if drivers either switch off the ACC or the CWA, miss warning messages or apply inadequate evasive manoeuvres. Besides, the fault tree risk model also shows the importance of the reliability of ADAS. Although further analysis on ADAS malfunction has not been carried out, it is believed that the reliability of ADAS itself and the quality of maintenance are likely contributing factors. It is well known that the maintenance of road vehicles is poor compared to other vehicles. These factors have effect on accident risk but are excluded from the event tree risk model.

The initiating event of this study involves two vehicles. However, the event tree and fault tree risk models only deal with the responsive behaviours of the following vehicle, including driver's and vehicular behaviours. This raises problems. First of all, it is known that the situations in the real world are dynamic and the relation between two vehicles is coupled. A collision may not occur even if the driver of the following vehicle does not react. For instance, the leading vehicle speeds up or changes lane before the following vehicle strikes it. Secondly, drivers are assumed only to have reactive behaviours in the static risk models. In fact, drivers are usually proactive and can predict upcoming situations and prepare for them. The first problem is dealt by using a micro-simulation model in this study. The second problem is still unsolved. The proactive feature of driver's cognition is still missing in the risk estimation method used in this study. This should be carefully awarded in the simulation of driver behaviours.

Only the longitudinal separation between vehicles is considered in this study. It makes sense to consider both longitudinal and lateral separation, in other words the avoidance of collisions. It is the overall phenomenon, i.e. accidents or collisions, that should be in the focus, not a single parameter as such. It is suggested that both longitudinal and lateral separation should be considered in future studies.

This study manipulates two variables in the car following model of RuTSim to simulate the possible behaviours of ADAS equipped vehicles. The method is not straightforward and is some what weird. It is because the study tried to adopt an existed micro-simulation model which is not originally developed for the purpose of safety evaluation. In other words, the proposed method is only a way to use the existed micro-simulation models in the assessment of traffic risk. The method is only an expedient and therefore must be revised. Indeed, what a micro-simulation model traffic safety needed is one which can reflect all the possible events of a risk model. It means that the development of a risk model must be done before the development a micro-simulation model and the micro-simulation model must base on the risk model. It is suggested in future studies that a micro-simulation model should have individual modules that models driver behaviours and ADAS functions.

7 Evaluation of safety effects of ADAS through traffic simulation

7.1 Introduction

Road safety is a major concern in most countries and continuous efforts are made in the design, implementation and evaluation of safety improving countermeasures. Traditionally, the main approach to improve road safety has been via passive countermeasures that are designed to reduce the consequences of accidents, e.g. seat belt laws, deformable road side equipment and improved vehicle crashworthiness. Today, the attention is turning towards active safety measures that are not only developed to reduce the consequences of accidents but also to reduce the number of driver errors and thereby the number of accidents. One important type of active safety measure is Advanced Driver Assistance Systems (ADAS). Examples of ADAS include Intelligent Speed Adaptation (ISA), Adaptive Cruise Control (ACC) and Collision Avoidance Systems (CAS). In many countries, most fatal road traffic accidents occur on rural highways. Improved safety on rural highways is therefore of great importance. In addition, the road mileage is in most countries dominated by rural roads. Any large scale implementation of passive infrastructure based safety, improving countermeasures for rural roads, is as a consequence very expensive. ADAS on the other hand, offers a cost effective way of increasing safety on the vast rural road mileage.

To assure real road safety improvements a priori estimation of the expected impact of the proposed safety countermeasure is necessary regardless of the type of safety countermeasure. This impact assessment should start from an individual driver perspective since ADAS give support to individual drivers. In addition, the relationship between changes in individual driver behaviour and the impact on the traffic system must be established in order to obtain an estimation of the overall safety impact of the ADAS. As this estimation of traffic system effects should be performed prior to large scale implementation of the ADAS, modelling of the traffic system becomes necessary.

Traffic micro-simulation models have proven to be useful tools in the study of various traffic systems. Although the most common application of traffic micro-simulation is level-of-service studies of different road design and traffic control strategies, previous research has also indicated that traffic simulation can be of use in road safety assessments (Barcelo et al, 2003; Archer, 2005; Minderhoud et al, 2001; Gettman et al, 2003). Since traffic micro-simulation models consider individual vehicles in the traffic stream, it is possible to extend the models to include ADAS-equipped vehicles. Simulation of traffic, including ADAS-equipped vehicles have been performed by several scientists, (e.g. Minderhoud, 2001; Liu et al, 2004; Hoogendoorn, 2005). In these works, the system functionality of certain ADAS, e.g. the ACC control function or the ISA speed limiting algorithm, has been modelled in detail. Changes in driver behaviour due to the ADAS are on the contrary usually not considered. Behavioural studies of driver's in ADAS-equipped vehicles have however shown that drivers will change or adapt their behaviour when supported by ADAS (Saad et al, 2004). Observed changes in driver behaviour include changes in reaction times, desired speeds and following distances.

This section considers assessments of the traffic system effects of ADAS based on traffic micro-simulation. The purpose of this chapter is to describe necessary features of a traffic simulation model to be used for ADAS safety evaluation and to propose a car-following model that allows inclusion of both ADAS system functionalities and driver behaviour for ADAS-equipped vehicles. Support of the longitudinal control part of the driving task has been identified as the ADAS area with the largest expected safety benefit (Ehmanns et al, 2004). This expectation is based on which accident types different ADAS can mitigate.

The longitudinal control part of the driving task is in a micro-simulation model controlled by a car-following model. The focus is therefore the requirements imposed on the car-following modelling. The proposed car-following model has been implemented in the Rural Traffic Simulator (RuTSim) (Tapani et al, 2005). The extended RuTSim model may then be used to assess the safety impact of ADAS in rural road environments.

The remainder of this section is organized as follows. Section 7.2 gives an overview of ADAS, including both system functionalities and observed changes in driver behaviour due to particular ADAS. Safety related traffic measures that can be derived from a micro-simulation model are also presented in this section. Section 7.3 contains a discussion on requirements placed upon a car-following model to be used for simulation and in road safety assessments of traffic, including ADAS-equipped vehicles. Moreover, a car-following model designed to meet these requirements is also proposed to complete this section. Section 7.4 presents simulation runs with the proposed car-following model, including a study of the sensitivity of some safety related traffic measures to differences in driver behaviour. Section 7.5 ends the chapter with conclusions and some further research directions.

7.2 ADAS and safety related traffic measures

Simulation of ADAS-equipped vehicles and safety evaluation of ADAS, place specific requirements on the simulation model. These requirements are dependent on the characteristics of the ADAS to be simulated. This section provides an overview of ADAS in general including ADAS functionalities and observed changes in driver behaviour. The level-of-service indicators normally derived from traffic simulation models are blunt tools for road safety assessments of ADAS. A traffic simulation model that traces individual vehicles in the traffic stream does however offer possibilities to derive other traffic measures more suitable for safety evaluations. This section also presents examples of such traffic measures.

7.2.1 Advanced Driver Assistance Systems

ADAS can be divided in to sub-categories depending on which part of the driving task the ADAS is supporting. One categorization that can be made is the following *(Flodas et al, 2005):*

- *Lateral control:* Lateral control ADAS include lane keeping aids and lane change collision avoidance systems. These systems improve road safety by prevention of unintentional lane departures or lane changes. Changes in driver behaviour that needs to be investigated are for example changes in lane changing or overtaking behaviour.
- *Longitudinal control:* Longitudinal control ADAS include Intelligent Speed Adaptation (ISA), Adaptive Cruise Control (ACC) and Collision Avoidance Systems (CAS). ISA systems are designed to control vehicle speeds. Vehicles are commonly guided towards keeping the speed limit. ACC systems support the distance keeping parts of the driving task. CAS are aimed at preventing collisions with surrounding objects in different situations. Observed changes in driver behaviour due to longitudinal control ADAS include changes in desired speeds, following distances and reaction times (Saad et al, 2004).
- *Parking/reversing aids:* Parking and reversing aids are systems that detect obstacles in low speed situations. These ADAS will not have any impact on road safety and are therefore not of interest within the context of this deliverable.
- *Vision enhancement*: Vision enhancement systems support drivers in situations with reduced visibility. Possible changes in driver behaviour for these systems are the same as the changes observed for longitudinal control ADAS.
- *Driver monitoring:* Driver monitoring systems are focused on the driver's physiological status. These systems are not aimed at assisting the driver in any part of the driving

task but rather to give information in situations when the driving task cannot be adequately performed by the driver.

- *Pre-crash systems:* Pre-crash systems are systems that pre-activate the vehicle's safety systems, e.g. seat-belts and air-bags, when an accident is unavoidable. The driver has no possibility to interfere with the system and behavioural changes are unlikely since the system kicks in when an accident is unavoidable.
- *Road surface/low-friction warning:* Road surface or low-friction warning systems give warnings to the driver in case of poor road conditions. The warning system may also be connected to an ISA system and guide the driver towards an appropriate speed given the current road condition. Possible changes in driver behaviour relevant for these systems are the same as the behavioural changes described for longitudinal control ADAS.

Today, the commercially available ADAS include mainly longitudinal control ADAS and parking aids. Lateral control ADAS are considered to be close to the market while other ADAS are still under early research and development (Flodas et al, 2005).
Traffic simulation will be of use for evaluation of ADAS that have an impact on the behaviour of individual vehicles and therefore also on the traffic system as a whole. All of the ADAS listed above except parking aids and pre-crash systems are likely to have such an impact on vehicle behaviour. A traffic simulation model to be used for ADAS evaluation should take into account both the system functionality of the ADAS and the behaviour of drivers in ADAS-equipped vehicles. The ADASE II project has identified longitudinal control ADAS as the ADAS category with the largest expected safety benefit (Ehmanns et al, 2004). The following work in this paper is for this reason focused on requirements imposed on the traffic simulation model by longitudinal control ADAS.

7.2.2 Safety related traffic measures

Several authors have derived traffic measures for road safety assessments from micro-simulation models. Such measures suitable for assessments of intersection safety are studied in (Getmann et al, 2004). In (Barceló et al, 2003) an "unsafety density" measure is derived and applied in simulations of motorway ramps. This safety measure is based on *leader-follower* vehicle pairs and assumptions of the follower's reaction time and the leader's deceleration capabilities. Safety measures for road sections based on time-to-collision trajectories of *leader-follower* vehicle pairs are derived in Minderhoud et al, (2001).

In the context of this work, a suitable safety measure should be applicable to road sections since longitudinal control ADAS are not limited to specific locations such as intersections. In addition, the safety measure should not be based on assumptions on vehicle/driver behaviour since ADAS will have an impact on vehicle/driver behaviour and therefore also on safety indicators based on behavioural assumptions. The safety indicators derived in Minderhoud et al, (2001) are for these reasons appropriate for assessments of longitudinal control ADAS. Other measures based on, for example, utilized deceleration rates could also be suitable for this task.

The safety measures derived in Minderhoud et al, (2001) are based on the notion of time-to-collision, TTC. TTC is defined as the time left to a collision with the vehicle in front if the speed difference between the vehicle and its leader is maintained. In Minderhoud et al, (2001), TTC with respect to the vehicle in front for each vehicle in every simulation time step are recorded. TTC trajectories for individual vehicles travelling on a road section are then computed from these recordings. Safety related traffic measures can be derived from the TTC trajectories by defining a TTC threshold, TTC^*, that separates safety critical situations from situations in which the driver remains in control. One measure of the total time spent in safety critical situations is Time Exposed TTC , which is defined as

$$TET = \sum_{i=1}^{N} \sum_{t=0}^{T} \delta_i(t) \cdot \tau, \tag{1}$$

where

$$\delta_i(t) = \begin{cases} 1, & 0 \le TTC_i(t) \le TTC^*, \\ 0, & \text{otherwise,} \end{cases}$$

$TTC_i(t)$ is the TTC of vehicle i in time step t. The simulation time step is denoted τ , N denotes the total number of vehicles and T is the simulation horizon.

The severity of the critical situations can be measured by Time Integrated TTC defined, using the same notation as in equation (1), as

$$TIT = \sum_{i=1}^{N} \int_{0}^{T} (TTC^* - TTC_i(t)) \cdot \delta_i(t) dt. \tag{2}$$

The TTC based safety indicators, TET and TIT , are illustrated in Figure 15. The TTC trajectory for vehicle i in the figure is shown for three closing in situations with finite TTC. Two of these situations become safety critical as TTC values below TTC^* have been recorded. The TET indicator for vehicle i is the sum of the time travelled with sub-critical time to collision and the TIT indicator is the sum of the shaded areas.

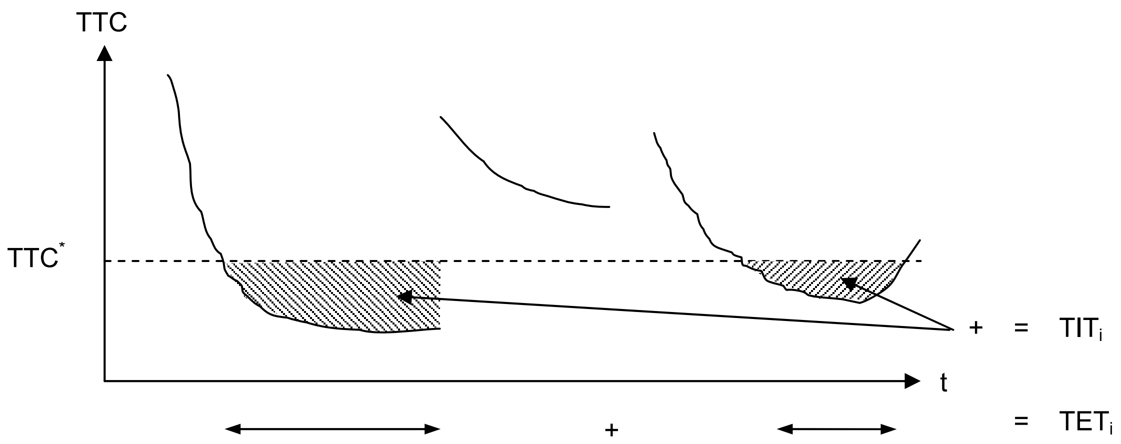

Figure 15 Time-to-collision trajectory and corresponding TTC based safety measures

7.3 A Car-Following model for evaluation of ADAS

The longitudinal control part of the driving task is in a traffic simulation model described by a car-following model. Simulation of longitudinal control ADAS does consequently impose requirements on the car-following modelling. In this section we first discuss these requirements and then propose a car-following model for simulation of ADAS-equipped vehicles.

7.3.1 Model requirements

An ADAS has an impact on traffic through its system functionality and through changes in driver behaviour due to the ADAS. A car-following model to be used in simulations of traffic, including ADAS-equipped vehicles, should therefore incorporate both of these aspects.

The system functionalities of longitudinal control ADAS include for example the ACC distance controller or the ISA speed limiting algorithm. These systems may accelerate or decelerate equipped vehicles using system specific acceleration rates. There may also be a certain delay in the reactions of the system. In addition, some systems only support the driver under certain traffic situations, e.g. standard ACC system only work at speeds above a certain threshold corresponding to free flow traffic conditions. All of these aspects should be taken into account in a car-following model for ADAS evaluation.

It has been observed that drivers in vehicles equipped with longitudinal control ADAS, change reaction times, following distances and speeds. The car-following model should therefore include parameters that control these driver properties. Other issues that deserve modelling attention are driver reactions at the boundaries of the functional area of the ADAS. For example, driver reactions when the ADAS takes over parts of the driving task and reaction delays when parts of the driving task are given back to the driver. To include the behaviour found among real drivers with and without the support of ADAS, the simulation model must also reflect differences between drivers as well as the inconsistency of one driver's actions in different situations.

7.3.2 A model to be used in simulation of ADAS equipped vehicles

We propose a car-following model with a flexible acceleration function, explicit reaction time modelling and a desired following distance in order to meet the requirements presented above. A flexible acceleration function is used to allow modelling of the acceleration of both unassisted drivers and ADAS-equipped vehicles. Explicit reaction times are needed to model ADAS that have an impact on vehicle reaction times, either as part of the system functionality or through changes in driver behaviour. The proposed car-following model does also include a controllable desired following distance, as changes in following distances have been observed for drivers in ADAS-equipped vehicles.
The car-following model specifies the acceleration rate for a constrained vehicle as a function of the distance to the vehicle in front. If the space headway to a vehicle in front is longer than a threshold T_o, the vehicle is considered to be free driving and a free vehicle acceleration model should be used to determine the acceleration rate of the vehicle. The headway threshold is defined as:

$$T_o = T_d \cdot v_{n-1} + \frac{(v_n - v_{n-1})^2}{2a_o}, \tag{3}$$

where v_n is the speed of the considered vehicle, v_{n-1} is the speed of the vehicle in front and a_o is a parameter. Finally, T_d is the desired following time headway given by

$$T_d = T_n + \frac{l_{n-1}}{v_{n-1}}, \tag{4}$$

where l_{n-1} is the length of the vehicle in front and T_n is the desired following time gap of vehicle n. If the headway to the vehicle in front is shorter than the distance given by equation (3) the vehicle is considered to be constrained by the vehicle ahead and its acceleration rate is determined by the car-following model. If the headway to the vehicle in front is shorter than another threshold, T_e, the vehicle is determined to be in an emergency deceleration state. In the emergency deceleration state a deceleration rate is used that is sufficient to prevent collision with the vehicle in front. The basic form of the acceleration function used when the headway to the vehicle in front is between T_o and T_e is an asymmetric Gazis-Herman-Rothery type function. That is, the applied acceleration rate is a function of the speed difference and the space gap between follower and leader and different functions are used in acceleration and deceleration situations (Olstam et al, 2004). If the headway to the vehicle in front is shorter than the desired headway given by equation (4) the vehicle should decelerate in order to extend the distance to the vehicle in front. In such situations, a deceleration rate that is always larger than or equal to the engine deceleration rate, is used to extend the distance to the vehicle in front. In summary, the acceleration rate specified by the car-following model is given by the following expression:

$$a_n(t+\tau_n) = \begin{cases} \min\left(\alpha v_n^{\beta} \dfrac{\left(v_{n-1}-v_n\right)}{\left(x_{n-1}-x_n-l_{n-1}\right)^{\gamma}}, d_n^{engine}\right), & T_e \le T < T_d \\ \alpha v_n^{\beta} \dfrac{\left(v_{n-1}-v_n\right)}{\left(x_{n-1}-x_n-l_{n-1}\right)^{\gamma}}, & T_d \le T \le T_o, \end{cases} \tag{5}$$

where T is the current headway to the vehicle in front, x_n is the position of the considered vehicle, x_{n-1} is the position of the vehicle in front, l_{n-1} is the length of the vehicle in front, d_n^{engine} is the engine deceleration rate and α, β and γ are model parameters. Different parameter values are used for acceleration and deceleration situations, i.e. acceleration parameters are used if $\operatorname{sgn}\left(v_{n-1}-v_n\right) \ge 0$ and deceleration parameters are used otherwise.

If the acceleration rate given by equation (5) is larger than the acceleration rate prescribed by the free vehicle acceleration model used in the simulation, it is not desirable for the follower to adopt the car-following acceleration rate. In such cases the acceleration rate specified by the free vehicle acceleration model is applied, even though the headway to the vehicle in front is shorter than the threshold given by equation (3). Moreover, if the vehicle is moving faster than its desired speed, it is not desirable to accelerate although equation (5) prescribes a positive acceleration rate. The free vehicle acceleration model is therefore used to decelerate vehicles in such situations.

In simulations including ADAS-equipped vehicles, the parameters of equation (5) should be set to reflect the acceleration behaviour of the modelled ADAS. Distributions of desired following time gaps and reaction times for vehicles equipped with specific ADAS should also be utilized. It may also be appropriate to use different driver/vehicle behaviour for different traffic situations, e.g. based on vehicle speeds. These behavioural driver/vehicle data can be obtained from the system specifications of the ADAS to be simulated, together with driving simulator or instrumented vehicle studies of drivers in ADAS-equipped vehicles.

7.4 Computational results

The car-following model described in the previous section has been included in the RuTSim model (Tapani, 2005). The standard car-following model of RuTSim, is replaced by the proposed car-following model for ADAS evaluation. RuTSim is a traffic micro-simulation model for rural road traffic. The model has been used for, among other things, studies of road design and traffic control alternatives.

Simulation runs with varying driver reaction times and desired following distances have then been performed using the extended RuTSim model to study the importance of changes in driver behaviour when simulating traffic including ADAS equipped vehicles for safety evaluation purposes. The aim of the simulation study is to investigate the potential to use traffic simulation for ADAS safety evaluation and to study necessary features of a traffic simulation model to be used for this task. The safety impacts of different reaction times and following distances has been studied through the extended time-to-collision safety measures presented above in equations (1) and (2), i.e. TET and TIT. The TET and TIT measures where chosen due to their ability to indicate road safety on a stretch of road. Other measures based on, for example, maximum deceleration rate could also have been appropriate for this task. Values of the car-following model parameters α, β and γ in equation (5) published by Yang (1997) were used in all simulations.

In order to permit simulation of traffic including vehicles with different behaviour, the traffic generation process of RuTSim has been modified to allow individual vehicle reaction times and desired following time gaps. For each vehicle type, i.e. cars and different types of trucks, the model allows specification of distinct categories with different reaction time and desired following time gap distributions. Vehicles are then generated according to these specifications. In a future simulation of traffic including vehicles equipped with different types of ADAS, different vehicle categories can be used to represent the impact of the ADAS.

7.4.1 Implementation

Driver reaction times are explicitly accounted for in the implementation. In a given time step, the model computes and stores the acceleration rate given by the car-following model and the acceleration rate stored in the time step one reaction time earlier is assigned to the vehicle under consideration. That is, vehicle reactions are delayed one reaction time. This procedure is used for all situations in which reaction times should be applied. When a following vehicle attains the speed of the vehicle in front and the distance to the leader is longer than the distance corresponding to the following vehicle's desired following time gap, acceleration rate zero is assigned to the following vehicle to model that the distance to the leader has been restored. The next reaction of the following vehicle is analogously delayed one reaction time, i.e. the acceleration rates given by the car-following model are stored and acceleration rate zero is used until one reaction time has passed. The following vehicle is allowed to react immediately in emergency deceleration situations to avoid collisions between vehicles. In such situations, reaction time is not applied until the distance to the leader is longer than the desired following distance.

7.4.2 Simulation runs

An existing 8 km long two-lane rural road in the southern part of Sweden has been modelled in the extended RuTSim model. The simulated road contained three intersections with left-turn lanes on the main road and three intersections without left-turn lanes. Traffic volumes corresponding to the average hourly traffic flow during 2004 were used for all simulation runs. The traffic flow contained cars and three types of trucks with and without trailer. The truck percentage of the traffic was approximately 15%. The critical time-to-collision threshold used for calculation of the TET and TIT indicators has been set to 3 seconds in all simulations. This value was chosen based on literature, see e.g. (Archer, MInderhoud), to distinguish safety critical situations from situations in which the driver remained in control.

Simulation runs with varying reaction times for cars was performed to isolate the impact of different reaction times on the safety indicators. Different reaction times can be thought of as corresponding to different types of ADAS. The reaction times of trucks were held constant at one second. This value was chosen to correspond to the reaction times of vehicles without any ADAS, i.e. the reaction time is a combination of the driver reaction time and the time lag between depression of the brake pedal and brake force application.

As a consequence, an indication of the impact of ADAS on surrounding unequipped vehicles is given by the relationship between the safety indicators for trucks and the reaction time of cars.

Figure 16 presents the resulting relationships between the reaction time and the safety indicators. The TET indicator shown in the left-hand side of Figure 16 has been normalized by average journey time, T_j, for the corresponding vehicle type. The TET indicator shown in the graph is therefore the percentage of the journey time travelled with sub-critical time-to-collision to the vehicle in front. In similar fashion, the TIT indicator displayed in the right-hand side of Figure 16 has been normalized by the average journey time multiplied by the critical time to collision threshold, $T_j \cdot TTC^*$. As a consequence, the TIT indicator shown in Figure 16 is a percentage of the maximum attainable TIT. The error-bars shown in the graphs indicate 90%-confidence intervals for the measures derived from the simulation. These confidence intervals have been constructed by assuming normally distributed output from simulations with different random number seeds. The difference in confidence interval width between vehicle types is due to the smaller proportion of trucks in the traffic stream. As a consequence, fewer trucks have been observed and the resulting confidence intervals become wider.

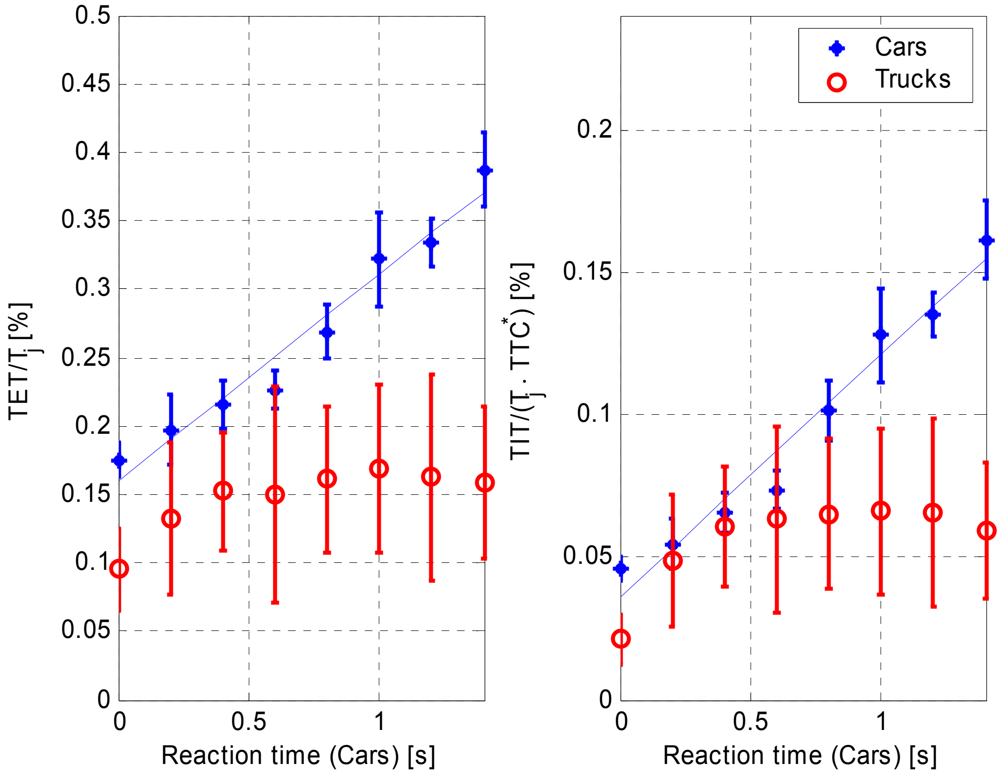

Figure 16 TET for cars and trucks as a function of the reaction time of cars (left) and TIT for cars and trucks as a function of the reaction time of cars (right).

The left-hand side of Figure 16 indicates a linear relationship between TET and reaction time for cars. The time travelled with a sub-critical time-to-collision is proportional to the reaction time. Hence, shorter reaction times will increase safety and ADAS that shorten reaction times may therefore improve road safety. Trucks do not appear to be influenced by changes in the reaction time of cars except for small reaction times. This indicates that an ADAS that reduces driver reaction time will have restricted impact on surrounding unequipped vehicles. However, if the ADAS result in very short reaction times then there may be an effect on the safety indicators for surrounding unequipped vehicles. One reason for this possible effect can be that if ADAS-equipped vehicles react very fast to situations ahead, there is more time for unequipped vehicles travelling behind to react before the critical situation is reached.

The right-hand side of Figure 16 shows similar relationships between TIT and reaction time. Consequently, as TIT can be viewed as a measure of the severity of the critical situations, the longer reaction times the more severe critical situations. The severity of the critical situations for trucks is not influenced by changes in the reaction time of cars except for short reaction times. There might be a tendency that the TIT indicator for trucks decreases with decreasing car reaction time for short reaction times. This may indicate, as discussed above, that ADAS that result in short reaction times may improve safety not only for the equipped vehicles but also for surrounding unequipped vehicles. The relationship between TIT and reaction time together with the evident relationship between reaction time and TET shown in left-hand side of Figure 16 indicates the importance of explicit reaction time modelling in a traffic simulation model to be used for ADAS safety evaluation.

Simulation runs with varying desired following time gaps for cars has also been performed to study the impact of this behavioural parameter. As in the experiment with varying reaction times presented above, different desired following time gaps can also be thought of as corresponding to different ADAS. Default desired following time gap distributions was used for trucks to allow interpretation of the safety indicator for trucks, as an indicator of the impact on surrounding unequipped vehicles.

Figure 17 depicts the resulting relationships between the desired following time gap for cars and the safety indicators. The TET and TIT indicators shown in the right- and left-hand sides of Figure 17 respectively, have been normalized in the same way as the indicators shown in Figure 16. The confidence intervals expressed by the error-bars in Figure 17 have also been constructed in the same way as the confidence intervals shown in Figure 16.

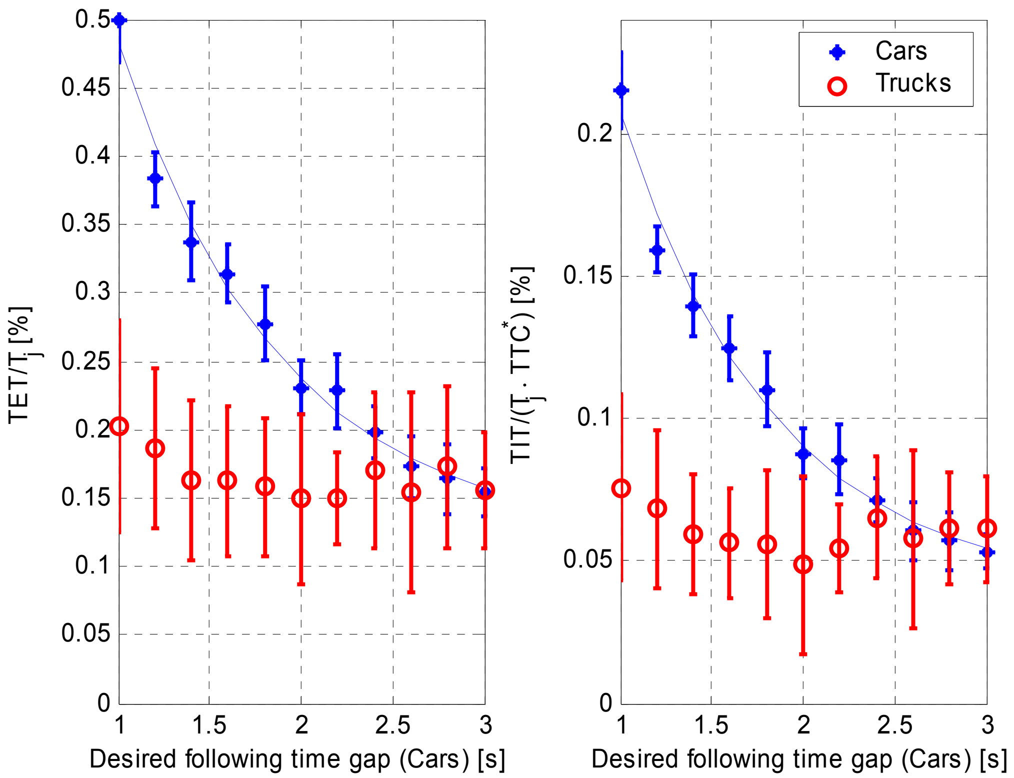

Figure 17 TET for cars and trucks as a function of the desired following time gap of cars (left) and TIT for cars and trucks as a function of the desired following time gap of cars (right).

The *TET* indicator increases exponentially with decreasing desired following distance. This indicates the importance of desired following time gap as a determining factor for the time travelled with sub-critical time-to-collision. As a consequence, ADAS that result in decreased following distances may also result in safety reductions if the decrease in following distance is not combined with, for example, a shortening of the reaction time. The *TET* indicator for trucks does not appear to be influenced by reduced desired following time gaps of cars, except for short desired following time gaps. The graph indicates that the *TET* for trucks may increase as the desired following time gaps of cars decrease for short desired following time gaps. For this reason, ADAS that result in very short following distances may also reduce safety for surrounding unequipped vehicles. This effect may be due to the fact that if an ADAS-equipped vehicle travels closer to its leading one, then the vehicle behind the ADAS-equipped vehicle is also likely to be closer to the vehicle in front of the ADAS-equipped vehicle. The vehicle behind the ADAS-equipped vehicle will therefore also have shorter time to react to any critical situation that may occur. As a consequence, care should be taken when designing ADAS that result in shortened following distances. It becomes very important to assess the effects on the traffic system as a whole in such situations.

The relationship between *TIT* and desired following time gap is shown in the right-hand side of Figure 17. The graph indicates that the severity of the critical situations increase exponentially with decreasing desired following time gaps. Trucks are not to any large extent influenced by decreased desired following time gaps of cars. As in the previously presented graphs, there is an indication that trucks may be affected by short desired following time gaps of cars. As both *TET* and *TIT* for cars increase exponentially with decreasing desired following time gaps, one may conclude that controllable desired following time gaps is an important feature of a traffic simulation model to be used for ADAS safety evaluation.

We have also studied average journey speed for cars as a function of reaction time and desired following time gap to compare the sensitivity of the *TIT* and *TET* indicators to the sensitivity of standard level-of-service measures derived from traffic simulation models. Figure 18 contains these relationships between journey speed and driver behaviour, expressed as reaction time and desired following time gap. The confidence intervals shown in Figure 18 have been constructed in the same way as the confidence intervals in the two previous figures.

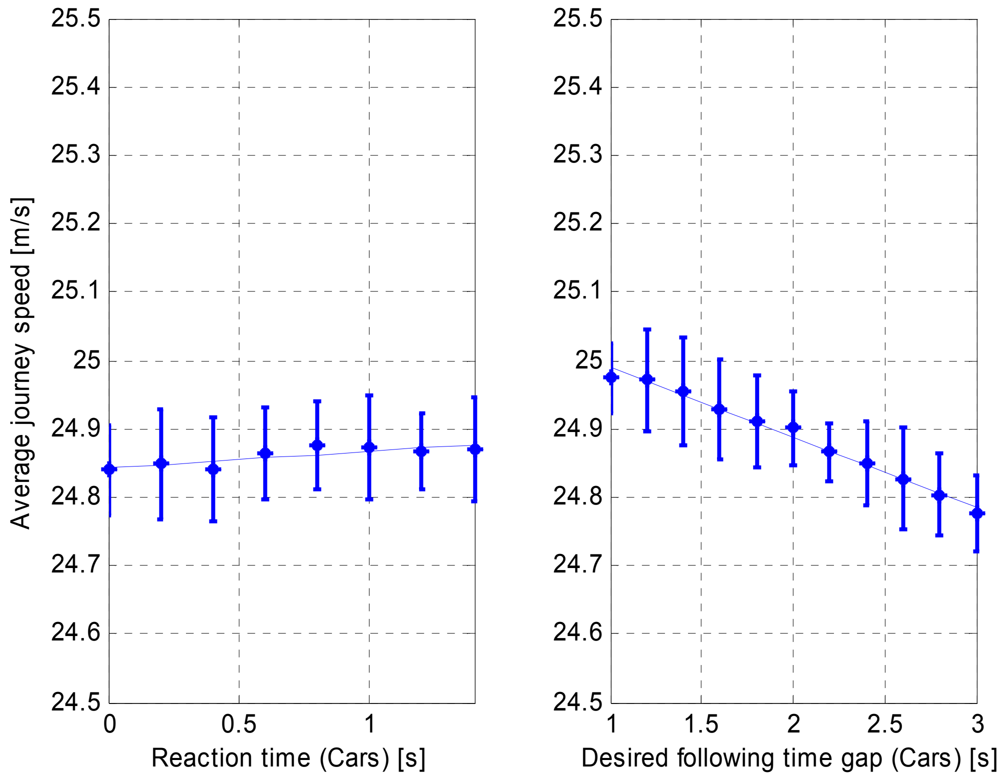

Figure 18 Average journey speed for cars as a function of the reaction time of cars (left) and the desired following time gap of cars (right).

As can be seen in the left-hand side of Figure 18, there is no clear relationship between reaction time and average journey speed. Therefore, it is not possible to draw conclusions on road safety due to changes in reaction time based on average journey speed. In addition, ADAS that only affect reaction times will not have any major consequences for the journey speed. The right-hand side of Figure 18 shows a tendency that increased desired following time gaps result in decreased journey speed. As a consequence, one may conclude that ADAS that have an impact on following distances will result in some changes in average journey speeds. However, the weak relationship indicates that average journey speed will be a blunt tool for safety assessments of ADAS that affect the desired following distance.

In summary, the results of the simulation runs indicate clear relationships between both reaction time and desired following time gap and the derived safety indicators. These findings indicate that traffic simulation will be of use in assessments of the safety effects of ADAS that have an impact on driver behaviour and the traffic flow properties.

7.5 Conclusions

Necessary features of a traffic simulation model to be used for safety evaluations of ADAS have been described. ADAS have an impact on traffic through the actual system functionalities and through changes in driver behaviour due to the ADAS. A traffic simulation model to be used for simulation of traffic including ADAS-equipped vehicles should therefore include both of these aspects. Changes in reaction times, following distances and speeds have been observed for drivers in vehicles equipped with longitudinal control ADAS. The car-following model used for simulation of longitudinal control ADAS should consequently allow modelling of these behavioural changes.

A car-following model including a flexible acceleration function, explicit reaction time and a desired following distance has been proposed for use in simulations of traffic including ADAS-equipped vehicles. Simulation runs with the proposed car-following model have been performed to study the impact of different driver/vehicle behaviour on safety related traffic measures derived from the simulation. The results show that driver/vehicle behaviour has a substantial impact on the derived safety measures. Modelling of driver/vehicle behaviour is therefore essential for reliable safety evaluations of ADAS.

The simulation runs presented in this work give inspiration for other tests. For example, it will be of interest to study different ADAS penetration levels by introducing additional vehicle categories with different driver behaviour. Another finding that demands further analysis is the sign of changes in the safety indicators for other vehicle categories, i.e. trucks in figures above, for short reaction times and following time gaps of cars. This may indicate that ADAS that shorten reaction times sufficiently, also provides safety benefits for surrounding unequipped vehicles. Analogously, ADAS that result in shorter desired following time gaps may also reduce safety for unequipped vehicles if not combined with a counteractive system that, for example, reduce driver reaction times.

The effect of many ADAS is likely to increase with increasing traffic volumes, as increasing traffic volumes also imply increasing interactions between vehicles. A study of the safety implications of ADAS under different traffic conditions would therefore be of interest. As reaction times and following distances are shown to have substantial impacts on the safety indicators it would also be interesting to study the impact of different values on the car-following model parameters. Modelling and simulation of specific ADAS are also subjects for future research. This work includes incorporation of system functionalities and observed driver behaviour for different vehicle types in the simulation model. The work described in this paper has focused on longitudinal control ADAS and requirements imposed on the car-following model. On two-lane rural roads without separation of oncoming lanes, there is also a potential to improve safety with ADAS that support overtaking carried through in the oncoming lane. The extended RuTSim model will be used to simulate traffic including such overtaking aids to assess this potential.

8 Discussion

This report provides a number of different methodologies for assessing the risk associated with various types of driving behaviour. First a literature review provided evidence for the varying risks as reported in observed on-road behaviour (naturalistic experiments). Secondly, a survey was performed where experts judged which behaviours (and combinations of behaviours) were deemed to be unsafe. Thirdly, a simulator experiment examined whether a methodological paradigm (the fixed-time schedule paradigm) could be used to estimate accident risk probabilities. Finally, the merits of using microsimulation are presented, along with a microsimulation experiment that evaluated some of the safety-related traffic measures of interest.

The literature review reveals there to be fairly robust studies that describe the nature of the relationship between speed, speed variability and accident risk. The remaining variables relating to lane keeping and car-following are less robust, and require further investigation. The Stated Preference survey attempted to estimate the relative importance of a number of driving variables. Experts were asked to judge the various driving scenarios in terms of safety and the coefficients were used to undertake a forecast analysis. The technique proved itself to be a useful way of ranking various behaviours and more importantly combinations of behaviours, with the proviso that these rankings are based on judgement only. The driving simulator experiment showed that drivers can be manipulated to perform at varying levels and hence to engage in varying levels of risk. The microsimulation modelling work showed great promise in its application to the evaluation of ADAS. RuTSim was used to simulate ADAS equipped vehicles by manipulating the car-following model. It is possible, however, that further work needs to be undertaken in order to refine other modules of driver behaviour.

Each of the methodologies used in this task have their own particular advantages and disadvantages. For example, microsimulation is the only modelling tool that is able to examine certain complex traffic problems (e.g. intelligent transportation systems, new or complex junctions, shockwaves, incident management). In addition, visually, microsimulation is attractive as it shows individual vehicles travelling across networks and can demonstrate problems and solutions in a comprehensible format. Microsimulation is particularly suited to the development, testing and evaluation of intelligent transportation systems (ITS), as long as they can reproduce individual driver behaviour. This can be the key disadvantage of microsimulation models - although microsimulation models provide predictions about network effects, their fundamental flaw is that, at present, the behaviour of the simulated vehicles is homogenous and inflexible. The vehicles follow simple rules in a deterministic manner, such as adhering to a two-second headway. The introduction of an ADAS into the microsimulation model does not take account of any interaction between the original rule set and the functioning of that intervention. That is, microsimulation does not take account of how drivers may change their own driving behaviour in response to the system. Such changes in behaviour may have important consequences for network safety. For example, if the ADAS is perceived by drivers to increase travel time as a result of speed limitation, then drivers may modify their "rules" and adopt a shorter headway to reduce travel time. It is therefore vital that changes in behaviour with the proposed ADAS are assessed in order to be able to provide these microsimulation models with realistic performance data. Such changes in behaviour can only be observed in on-road or simulator studies.

On-road and simulator studies can provide more naturalistic data and the experimenter also has the advantage of being able to interrogate the driver – thus providing a wealth of qualitative feedback. On-road trials, although they have the advantage of allowing the experimenter to observe driver behaviour close-hand, do not allow drivers to *interact* with other equipped traffic. In a mixed fleet, drivers may exhibit behaviour that would not occur if the total vehicle fleet were equipped. In addition, on-road trails are expensive and somewhat unpredictable, and sometimes ethical problems can arise. Driving simulator studies provide a halfway house – the traffic conditions are repeatable and controlled, yet various “critical” events can be introduced to evaluate risky driving behaviour. We suggest that an iterative procedure is used:

1. First, the basic driver reactions to an AIDE interface could be evaluated in a driving simulator. This is ethically sound and exposes drivers to no danger.

2. These driver behaviours can then be used to modify existing behavioural rules in the microsimulation models. Running the models then allows for data collection on a larger scale, taking the road environment into consideration.

3. On-road studies can then be carried out, safe in the knowledge that as many of the unpredictable risks can now be identified and catered for. Naturalistic driving with the AIDE system can be studied.

4. This could be an iterative process, depending on whether the on-road studies resulted in new behavioural rules that should be incorporated into the microsimulation model.

The work carried out in this task, has attempted to define the interrelationships of various behavioural parameters. This, along with the work carried out in the rest of the workpackage, will help to fulfil one of the main aims of AIDE – which is to minimise the level of workload and distraction imposed by in-vehicle information systems. By understanding which safety parameters are the most important, designers of the integrated system can ensure that the effects on these behavioural parameters are reduced. Thus the results from this task, will be a key input to the development of design guidelines and standards within sub-project 4.

9 Integration into the AIDE project

The work reported here is on relatively ‘pure’ relationships between behaviour and accident risk. Its results will be fed into the consideration of the next big issue, which is how behavioural effects trade off with driver state effects (question: who runs the most risk, a fully alert driver at speed 120 or a drowsy driver at speed 80?). This will be examined in Task 2.3.2/Deliverable 2.3.2. After that, the step from empirical data – the ones we usually generate in our studies – to real accident risk will almost be completed. We also offer our findings to SP 1 wholeheartedly, and hope they can find some clues in them that will help them to validate the models they are busy developing.

10 References

Archer, J. (2005). Indicators for traffic safety assessment and prediction and their application in micro-simulation modelling: A study of urban and suburban intersections. Department of Infrastructure, Royal Institute of Technology, Stockholm, 2005.

Archer, J. and Kosonen. I. , (2000). The potential of Micro-Simulation Modelling in Relation to Traffic Safety Assessment. Conference presentation, published in ESS Conference 2000 proceedings. CTR2000:07

Barceló, J., A.-G. Dumont, L. Montero, J. Perarnau and A. Torday. Safety Indicators for Microsimulation-based assessments. Presented at Transportation Research Board Annual Meeting 2003, Washington D.C., 2003.

Baruya, B. (1998). Speed-accident relationships on European roads. Staff Papers PA/SE/3956/03. TRL

Brookhuis, K. and de Ward, D. (2004). *ADAS' acceptance and effects on behaviour: the consequences of automation*, 3rd International Conference on Traffic and Transportation Psychology, 5-9 September, 2004, Nottingham, UK.

Brown, I.D. (1990). Drivers' margins of safety considered as a focus for research on error. *Ergonomics, 33(10/11),* 1307-1314.

Ehmanns, D. and H. Spannheimer (2004). *ADASE II Roadmap (ADASE Deliverable D2D Roadmap Development)*. Information Society Technologies, Brussels, 2004.

Evans, L. (1991). *Traffic safety and the driver*, (New York: Van Nostrand Reinhold).

Evans, L. & Wasielewski, P. (1982) Do accident involved drivers exhibit riskier everyday driving behavior? Accident Analysis and Prevention, 14, 57-64

Fairclough, S.H., May, A.J. and Carter, C. (1997). The effect of time headway feedback on following behaviour. Accident Analysis & Prevention, 29, 3, 387-397.

Farber. E. (1993). Using freeway traffic data to estimate the effectiveness of rear-end collision countermeasures. Washington, DC: proc. Third Annual Meeting of the Intelligent Vehicle Society of America.

Farber, E. (1994). Using the reamacs model to compare the effectiveness of alternative rear end collision warning algorithms. Paper Number 94 S3 O 03, XIVth International Technical Conference on Enhanced Safety of Vehicles, München.

Finch, D.J., Kompfner, P., Lockwood, C.R. & Maycock, G. (1994). Speed, speed limits and accidents. Project Record S211G/RB/Project Report PR 58. TRL.

Flodas, N., A. Admitis, A. Keinath, K. Bengler and A. Engeln (2005). *Review and Taxonomy of IVIS/ADAS applications (AIDE Deliverable D2.1.2)*. Information Society Technologies, Brussels, 2005.

Gettman, D. and L. Head Surrogate Safety Measures from Traffic Simulation Models. *Transportation Research Record*, No. 1840, 2003.

Godthelp, J. (1984). Studies on Human Vehicle Control. Thesis, Delft Technical University.

Hague Consulting Group (1992) ALOGIT Users' Guide: Version 3.2.

Hoedemaeker, M. (1999). Behavioral reactions to advanced cruise control: results of a driving simulator experiment. In R.E.C.M. van der Heijden & M. Wiethoff (eds.) *Automation of car driving – Exploring societal impacts and conditions* (Delft: Delft University Press).

Hoogendoorn, S.P. (2005). ADAS Safety Impact on Rural and Urban Highways. Presented at Transportation Research Board 2005 Annual Meeting, Washington D.C., 2005.

Jamson, A.H. and Merat, N (2005). Surrogate in-vehicle information systems and driver behaviour: Effects of visual and cognitive load in simulated rural driving. Transportation Research Part F 8 79–96.

Janssen, W.H. (2000). Functions relating driver behavior and accident risk. *(In Dutch).Soesterberg: TNO Human Factors, memo.*

Kay, G.G. (2000). The effects of antihistamine on cognition and performance. The Journal of Allergy and Clinical Immunology, 105 (6, 2), 622-627.

Keall, M.D., Povey, L.J. and Frith, W.J. (2002). Further results from a trial comparing a hidden speed camera programme with visible camera operation. Accident Analysis and Prevention. 34, 6, 773-777.

Kloeden, C.N., Ponte, G. & McLean, A.J. (2001). Travelling speed and the risk of crash involvement on rural roads. Report No. CR 204. Australian Transport Safety Bureau ATSB.

Koornstra, M. (1990). Analyse van veiligheidseffecten van veranderingen in snelheden: Een mathematisch-theoretisch analyse. Leidschendam, SWOV.

Lamble, D., Kauranen, T., Laakso, M. and Summala, H. (1999). Cognitive load and detection thresholds in car following situations: safety implications for using mobile (cellular) telephones while driving. Accident Analysis and Prevention 31, 6, 617-623.

Liu, R. and J. Tate. (2004). Network effects of intelligent speed adaptation systems. *Transportation*, No. 31,pp. 297-325.

Marschak, J. (1960) Binary choice constraints and random utility indicators. In Marschak, J. (1974) *Economic Information, Decision and Prediction: Selected Essays* (Volume 1). D. Reidel, Dordrecht.

Maycock, G., Brocklebanck, P.J. & Hall, R.D. (1998). Road layout design standards and driver behaviour. TRL report No. 332.

McFadden, D. (1976) Quantal choice analysis: a survey. *Annals of Economic and Social Measurement*, 5 (4), pp363-390.

Minderhoud, M.M. and Bovy. P.H.L. (2001). Extended time-to-collision measures for road traffic safety assessment. *Accident Analysis and Prevention*, No. 33, 2001, pp. 89-97.

Nilsson, G. (1982). The effects of speed limits on traffic accidents in Sweden. In: Proceedings of the international symposium on the effects of speed limits on accidents and fuel consumption, 6-8 October 1981, Dublin (OECD, Paris).

Nilsson, G. (1984). Speeds, accident rates and personal injury consequences for different road types. Linköping: VTI, Rept. VTI-277.

Nilsson, G. (1997). Speed management in Sweden. Linköping: VTI.

O'Hanlon, J.F., Vermeeren, A., Uiterwijk, M.M., van Veggel L.M. and Swijgman H.F. (1995). Anxiolytics' effects on the actual driving performance of patients and healthy volunteers in a standardized test. An integration of three studies, Neuropsychobiology 31 (2), pp. 81–88.

Olstam, J.J. and A. Tapani. *Comparison of Car-following models*. VTI, Linköping, 2004.

Ortuzar, J de D (2000) Stated Preference Modelling Techniques. Perspectives 4, London.

Philip, P., Sagaspe, P., Moore, N., Taillard, J., and Charles, A., (2005). Fatigue, sleep restriction and driving performance. Accident Analysis and Prevention 37(3) pp473-8.

Quimby, A., Maycock, G., Palmer, C. & Buttress, S. (1999). The factors that influence a driver's choice of speed: A questionnaire study. TRL report No. 325.

Ramaekers, J.G. and O'Hanlon, J.F. (1994). Acrivastine, terfenadine and diphenhydramine effects on driving performance as a function of dose and time after dosing. Eur. J. Clin. Pharmacol. 47 (3), pp. 261–266.

Rasmussen, J. (1982). "*Human Errors: A Taxonomy for Describing Human Malfunctions in Industrial Installations*". Journal of Occupational Accidents, 4, 311-335.

Roszbach, R. & Koornstra, M. (1991). Snelheidsbegrenzers voor vrachtwagens en bussen: Overwegingen bij de keuze van een maximum instelwaarde. Leidschendam: SWOV.

Rumar, K. (1990). The basic driver error: late detection. *Ergonomics, 33(10/11)*, 1281-1290.

Saad, F., M. Hjälmdahl, J. Cañas, M. Alonso, P. Garayo, L. Macchi, F. Nathan, L. Ojeda, V. Papakostopoulos, M. Panou and E. Bekiaris (2004). *Literature review of behavioural effects (AIDE deliverable D1.2.1)*. Information Society Technologies, Brussels, 2004.

Salusjärvi, M. (1990). In G. Nilsson (Ed.), Speed and safety: research results from the Nordic countries. Linköping: VTI.

Tapani, A. A Versatile Model for Rural Road Traffic Simulation (2005). Presented at Transportation Research Board 2005 Annual Meeting, Washington D.C., 2005.

Taylor, M.C., Lynam, D.A. & Baruya, A. (2000). The effects of drivers' speed on the frequency of road accidents. TRL Report No. 421.

Treffner, P.J. and Barrett, R. (2004). Hands-free mobile phone speech while driving degrades coordination and control. Transportation Research Part F 7, 4-5, 229-246

Van der Hulst, M., Rothengatter, T., & Meijman, T. (1999). The effects of reduced visibility and time pressure on drivers' distance-keeping behaviour. In A.G. Gale et al. (Eds), *Vision in Vehicles VII*, (Amsterdam: Elsevier Science), pp. 311-318.

Wilde, G.J.S. (1982). The theory of risk homeostasis: implications for safety and health. *Risk Analysis, 2*, 209-225.

Wilde, G.J.S. (1988). Risk homeostasis theory and traffic accidents: propositions, deductions and discussion of dissension in recent reactions. *Ergonomics,* 31, 4, 441-468.

Yang, Q. *A Simulation Laboratory for Evaluation of Dynamic Traffic Management Systems* (1997). Massachusetts Institute of Technology, Cambridge.