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Generalization of case studies in road traffic when defining pre-crash scenarios for active safety function evaluation

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ABSTRACT

To define pre-crash scenarios for evaluation of active safety functions, data from crash investigations is often used. Typical data sources include official databases with police reported crashes (macroscopic data) and in-depth case studies (microscopic data). Macroscopic data is often representative but has little detail on causation, while the opposite is true of microscopic data. Combining the sources by coupling causation information from a set of case studies to a macroscopic crash type would therefore seem ideal. For the coupling to be valid however, it must be verified that the selected case study set is representative of the crash type. The aim of this study is to describe and test a new methodology for such verification by means of an intermediate layer of representatively sampled crash information (questionnaire responses from crash involved drivers). The methodology was applied to intersection crashes. For the data sets used, the similarity in crash causation for case studies and questionnaire crashes, together with the context similarity for questionnaire crashes and the macroscopic crash type, was sufficient to argue that the case studies were representative of the crash type. While results must be considered preliminary given the limited data sets used, the proposed methodology shows promise for future work related to defining pre-crash scenarios for ADAS evaluation.

1. Introduction

The goal of preventive safety functions, or advanced driving assistance systems (ADAS), is to prevent crashes from occurring and/or to reduce crash severity, by either alerting the driver to potential hazards or by taking over the driving task to some extent, using, for example, autonomous braking in emergency situations. Examples of ADAS are forward collision warning (FCW) and lane departure warning (LDW).

To be able to evaluate the extent to which ADAS technologies prevent and/or mitigate crashes, it is essential to characterize the sequence of events which leads to collisions (Najm et al., 2002). Information on such sequences of events, or pre-crash scenarios, helps development of objective test procedures and guides collection of appropriate driver performance data with and without ADAS assistance (Kiefer et al., 1999), which is essential for the estimation of the ADAS safety benefits (Najm et al., 2000). Furthermore, to be relevant for development and evaluation of crash countermeasure concepts, it is also important that these pre-crash scenarios include information on causal factors (Najm et al., 1995).

It should be emphasised that this is not to say that the way forward in crash prevention will come solely from descriptions of things gone wrong. As many researchers argue, to further enhancement safety in complex dynamic systems such as modern road traffic, one must also understand how and why things go right. For example, while crash investigations may reveal where a driver's control processes have failed, the development of preventive countermeasures also depend on developing an understanding of how and why those control processes normally generate successful control. Without such understanding, monitoring and regulating risk associated variability and perturbations becomes very difficult. For further discussions of this topic, see, for example, Dekker (2002, 2005), Hollnagel (2004), Hollnagel et al. (2006) and Ljung Aust and Engström (in press).

Data from crash investigations is often used to identify and characterize pre-crash scenarios for ADAS evaluation. Crash data typically comes from either official databases containing police reported crashes or from in-depth case studies. The former is often referred to as *macroscopic data* while the latter is referred to as *microscopic data* (OECD, 1988). A typical example of macroscopic data is the annual compilation of information from all police reported vehicle crashes in Sweden performed by the *Swedish Institute for Transport and Communications Analysis* (SIKA) (see, for example, SIKA, 2007). Macroscopic data is often statistically representative of crashes occurring in a defined region due to the number of crashes collected and the sampling strategy applied, but contains limited information on why crashes happen (Larsen, 2004; Sabey, 1990).

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Microscopic data on the other hand is rarely representative, due to the extensive resources needed for in-depth investigations (requiring on-scene inspections, driver interviews, reconstruction of vehicle kinematics, etc.), but does provide ample data on why the investigated crashes took place. A typical example of microscopic data are the crash causation charts created through detailed, on-scene, multidisciplinary investigations of contributing factors in vehicle crashes in the European project *Building the European Road Safety Observatory* (SafetyNet) (SafetyNet, 2005, 2008). According to Larsen (2004) and Midtland et al. (1995), qualitative in-depth crash information is the best source for identifying interactions between crash contributory factors, i.e. for defining crash causation mechanisms.

Ideally, macroscopic and microscopic data would therefore be used as complements. A macroscopic data source could be used to identify a statistically significant crash type, and microscopic data could provide details on why crashes of that type take place. The result would be a statistically valid pre-crash scenario description which is also rich on crash causation details. However, current principles used to match in-depth case studies to a macroscopic crash type suffer some drawbacks. One common approach, which can be called the context matching approach, is to start from macroscopic data (see, for example, Chovan et al., 1994; General-Motors-Corporation, 1997; Tijerina et al., 1994). One first characterises a crash type using context variables found in macroscopic data. Context variables here refers to variables which describe the circumstances under which a crash has occurred, but which do not relate to causation, e.g. road type, vehicle type, etc.[1] Examples of crash types include "lane change left" and "struck animal" (General-Motors-Corporation, 1997). The context properties of the crash type are then used to identify cases in a microscopic data source which have occurred in a similar context. The selected cases are analysed for crash contributing factors, and those contributing factors are then inferred to be typical for all crashes of that type.

The problem with this approach is that even if a set of case studies occur in a context similar to that of a macroscopic crash type, it cannot a priori be concluded that their causation mechanisms are typical for the crash type. The devil's advocate would argue that for all we know, the contributing factors in the case studies could be exceptions rather than the norm. A more robust way of coupling the case studies to the macroscopic crash type, which also takes contributing factors into account, would therefore be helpful.

Another approach to defining pre-crash scenarios is prototype scenarios (Fleury and Brenac, 2001). A prototypical scenario is an abstract representation of the main characteristics in a group of similar accidents rather than a specific representation of any particular accident. Using a microscopic data source, one first groups the case studies it contains based on their similarity in terms of context properties and causal relationships. Next, a prototypical scenario is built for each group by identifying the main features of the group. For examples, see the work carried out in the European project *Traffic Accident Causation in Europe* (TRACE) by Naing et al. (2007) and Van Elslande and Fouquet (2007a,b).

The drawback with this approach is that as long as the microscopic data source does not contain representative data, prototypical scenarios built from it cannot claim representativity either. Also, since the identification of typical contributing factors and circumstances is based on researcher judgment, each scenario will be associated with a measure of subjective interpretation. According to Fleury and Brenac (2001), a systematic examination of how to establish the link between prototypical scenarios and crash types in macroscopic data is needed, as well as more automatic classification methods which are less dependent on researcher's judgment.

The main objective of this study is to propose a new way of assessing whether causation information from microscopic data is representative of a macroscopic crash type, which may overcome the difficulties faced by the context matching and prototype scenario approaches. A methodology for linking case studies to a macroscopic crash type by means of an intermediate layer of context and causation information will be described and tested. A secondary objective is to address the subjective classification problem in the prototypical scenario approach.

The methodology is tried out on intersection crashes. These crashes are frequent and costly both in terms of injury and property value (NCSA, 2007; SafetyNet, 2007; SIKA, 2007). Also, due to difficulty of addressing them with vehicle based countermeasures, they have received less attention in ADAS development compared to, for example, rear end collisions and lane departures which usually present a less complex driving situation. However, as these other areas are maturing, ADAS developers are now turning their interest toward intersection crashes, and a number of proposed countermeasures will likely need evaluation not too far into the future.

2. Methodology

The new methodology proposed, called *integrated cause and context matching*, can be viewed as a modification and extension of the context matching approach described above. A statistically representative crash type is identified in macroscopic data, and information on contributing factors for that crash type is sought in other data sources which contain more detailed information on crash causation. However, in addition to retrieving causation information from a typical microscopic data source (here: in-depth case studies); causation information is also retrieved from a data source designed to have a combined microscopic and macroscopic character.

This data source, which for want of a better term can be called micro–macro-data, consists of questionnaire responses from crash involved drivers. Questionnaires can be designed to capture crash causation information on a more detailed level than typically found in macroscopic data. They are also less costly to collect than case studies, so they can more easily be collected according to a sampling plan and in numbers which makes them representative of a defined region. This means that when a subset of questionnaires are selected as matches to a macroscopic crash type, the information contained in that subset can be considered representative of the crash type (if sampling has been correct and sufficiently extensive).

Since this includes the information it contains on crash causation, causation patterns in the subset of questionnaires can be used to assess the representativity of causation patterns from case studies which also match the crash type, given that the questionnaire causation information is rich enough to be analysed in a way similar to how the case studies are analysed. Similar questionnaire and case study causation patterns would indicate that the contributing factors identified in the case studies are typical for the crash type. If causation patterns differ, this would indicate that the case studies are not typical. Used this way, the questionnaire data can function as glue, or a bridge, between crash causation patterns found in a set of case studies and a crash type identified in macroscopic data.

This study was carried out according to the following procedure (also depicted in Fig. 1 below). First (1), a crash type was selected from a statistical study based on macroscopic data. Next (2), case studies matching that crash type were retrieved from an in-depth

[1] Note that the classification of a variable as context describing or crash contributory is not fixed. Rather it depends on the way contributing factors are conceptually viewed by the classifying researchers. For example, some may view ice on the road as a crash cause rather than as crash context.

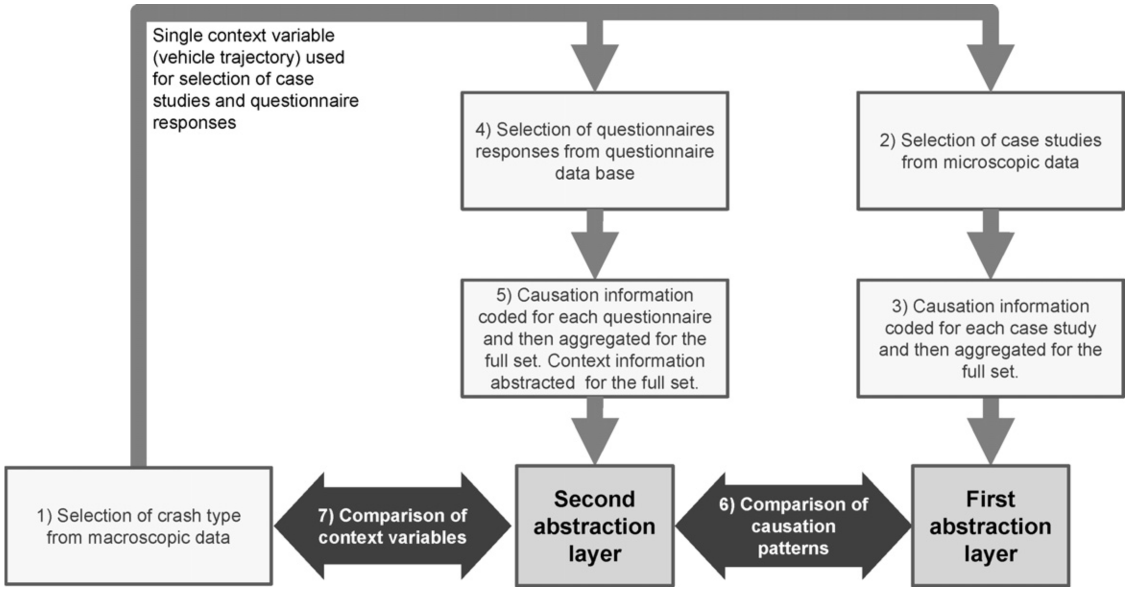

Fig. 1. Illustration of the flow of work using the integrated cause and context matching approach.

crash investigation project. For each in-depth case study, the pattern of crash contributing factors was identified (3). The individual patterns were then compiled into an aggregate pattern representing the whole set of selected case studies, below referred to as the *first abstraction layer*. For details of this process, see Section 2.2 below.

Next, a second abstraction layer created was created from micro–macro-data, using a similar procedure. A questionnaire was developed and sent out to crash involved drivers. Matches to the macroscopic crash type were identified among the responses (4), and for each of those, a pattern of crash contributing factors was identified (5). The individual patterns were then compiled into an aggregate pattern of crash contributing factors representing the whole set of selected questionnaires, below referred to as the *second abstraction layer*. While multiple researchers were involved in the coding of causation information for the case studies, all coding of causation information in the questionnaires was done by a single researcher (the author). Potential implications of this are discussed in Section 4.4.

When the first and second abstraction layers had been created, their respective patterns of crash contributing factors were compared to assess their similarity (6). The comparison was both quantitative and qualitative. The quantitative comparison focused on the presence and relative frequency of appearance of contributing factors in both layers. For each contributing factor, the number of times it appeared in an aggregated chart was divided with the total number of contributing factors in that chart. This gave each contributing factor an appearance percentage which could be plotted for comparisons. The qualitative comparison focused on similarities and differences in the patterns of contributing factors displayed by first and second abstraction layers.

Now, even if the abstraction layer comparison show causation patterns to be similar, an inherent possibility is that the macroscopic and micro–macro-data sources sample different crash populations, though both are representatively sampled in their own way, something which could call the link between the second abstraction layer and the macroscopic crash type into question. The final step was therefore to assess crash population similarity for the macroscopic and micro–macro-data sources (7). While there are many ways to do this, the background of this study is characterization of pre-crash scenarios for ADAS evaluation. In relation to that, a pragmatic approach is to compare context characteristics of the macroscopic crash type and the micro–macro-data subset. If these are similar, then for the practical purpose of defining pre-crash scenarios, they can be considered to sample the same crash population. In this study, the context variables *state of the road*, *weather*, *speed limit*, *light conditions*, *gender* and *age* were used to compare questionnaire crashes with the macroscopic crash type.

It is worth noting that to keep the final context comparison (step 7 above) as unbiased as possible, the procedure for selecting crashes matching a macroscopic crash type was slightly modified in this study, compared to, for example, General-Motors-Corporation (1997). Rather than using several context variables to characterize the crash type which cases from other data sources should match, only a single context variable (vehicle trajectories) was used.

2.1. Data sources

There are three data sources used in this study, one macroscopic, one micro–macro and one microscopic. An overview is provided in Table 1, with more details given below.

2.1.1. Macroscopic data

In this study, the macroscopic data comes from a statistical study carried out at Volpe National Transportation Systems Center to describe crossing path crashes in the US (Najm et al., 2001). These crashes usually occur at intersections, but may also occur at driveways. The researchers developed a crash typology which sorts crashes into groups based on actual and intended vehicle trajectories prior to the crash, and queried the *General Estimates System* (GES) (NCSA, 2005), a crash database which is representative of vehicle crashes occurring in the US, for numbers on each crash type.

One reason for selecting this typology is that vehicle trajectories are coded in all the data sources used for the study, thus simplifying selection of cases matching the selected macroscopic crash type. Another reason is that if study results are to be used for pre-crash scenario definitions in ADAS evaluation, vehicle trajectories provide a natural frame of reference for the ADAS developers. To limit the scope of this study, the subtype of intersection crashes called Left Turn Across Path–Opposite Direction (LTAP/OD) was selected for further analysis (see Fig. 2).

Table 1
Data sources used in the study.

Data source	Data type	Sampling	Coverage	Method of investigation
GES	Macroscopic data	Probability sample of motor vehicle crashes covering crashes of all severities and all vehicle types in the United States	Nationally representative sample for the United States	Police accident reports
FICA	Microscopic data	Motor vehicle crashes occurring in a limited geographical area, mostly on weekdays during daytime	Targeted single vehicle and intersection crashes, not representatively sampled	In-depth crash investigations conducted on-scene by a police independent, multidisciplinary team
Questionnaire data	Micro–macro-data	Questionnaires sent to crash involved Volvo car drivers	Nationally representative of crashes with Volvo cars in Sweden	Questionnaire sent to owners of Volvo cars involved in crashes with implied repair costs over 4500 Euro

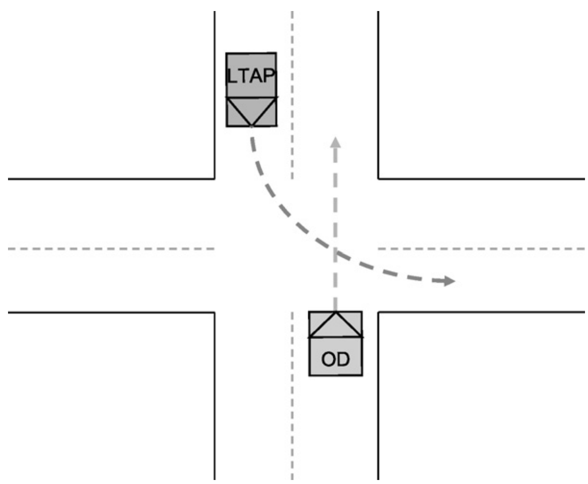

Fig. 2. The LTAP/OD conflict pattern in the intersection crash typology developed by Najm et al. (2001).

The typical scenario for an LTAP/OD crash is a left turning vehicle cutting across the path of another vehicle coming from the opposite direction, and which intends to cross the intersection on a straight path. It represents 472 000 crashes, or 27.5% of all intersection crashes in the US (Najm et al., 2001). Since the report where the typology in Fig. 2 comes from primarily focuses on intersection crash type proportions, it contains limited information on other variables relevant to crash type description. However, more details on LTAP/OD crashes are given in a later report by Najm et al. (2007).[2] Data on contextual variables for LTAP/OD not present in the first study were therefore taken from the later study.

2.1.2. Microscopic data

In-depth case studies for this study come from the Swedish in-depth study project *factors influencing the causation of accidents and incidents* (FICA) (Ljung et al., 2007). Approximately 200 motor vehicle crashes were investigated in the period August 2003–December 2006. Investigations were conducted on-scene by a police independent, multidisciplinary team. The investigations took place in a limited geographical area (mainly in and around Gothenburg, Sweden), mostly on weekdays during daytime. The investigation team was primarily focusing on single vehicle and intersection crashes (Sandin and Ljung, 2004, 2007), so the data set does not reflect a representative sampling plan. 17 intersection crossing path crashes between motor vehicles of the LTAP/OD type could be identified in the case files for further analysis.

2.1.3. Questionnaire data

Questionnaire data was collected in two rounds, both in the form of temporary expansions of the continuous crash data collection which has been ongoing at Volvo Cars since 1975. Crash data comes from crashes with Volvo cars in Sweden, model years 1967 until present day. Inspectors from Volvia (If P&C Insurance), the company with which all new Swedish Volvo cars are insured, identify crashes which imply repair costs over a certain limit (currently 4500 Euro, the sum has been adjusted over the years to keep the impact severity for different crash modes stable). Photos and technical details of the cars are sent to Volvo's Crash Research Team, and a detailed questionnaire is sent to the owner of the car to gather information about the crash, the car and the occupants, as well as consent forms for retrieval of medical records.

In addition to the standard questionnaire, a complementary questionnaire was sent out in the time period May 2004 to August 2005 to drivers who indicated they had crashed at an intersection. The complement was designed to capture causation information in a way similar to how causation data was collected in the FICA project, using the FICA project driver interview guide as guidance (Ljung et al., 2005). After evaluation of responses to the first complementary questionnaire, a slightly modified version of the complement was sent out in the time period December 2006 to March 2008. Response rates were 39% in the first round and 49% in the second round of questionnaire collection, the potential implications of which are discussed in Section 4.4. For both rounds, context variables similar to those found in GES (NCSA, 2005) were identified in the driver's responses to the standard questionnaire.

The questionnaire data in total contains 438 reported intersection crashes. 57 are of the LTAP/OD type, with 31 drivers on a LTAP trajectory and 26 drivers on an OD trajectory. These are low numbers compared to Najm et al. (2001), and closer to crash numbers typical for microscopic than macroscopic data sources. For the intent of this study, i.e. to test the feasibility of the proposed methodology, the data set is sufficient, because it is representatively sampled. However to claim statistical significance for the questionnaire data set findings, a larger sample would be required. Exactly how large depends on several factors and will not be addressed here.

2.2. Details on the creation of the first and second abstraction layers

To create the first abstraction layer, details on crash contributing factors for each driver in each in-depth study case file were first coded using the driving reliability and error analysis method (DREAM) (Ljung, 2002; Ljung et al., 2005). DREAM is an adaptation

[2] The reason for not using only the later report is that the authors there modified the crash typology, mixing vehicle trajectories with causation related selection criteria for crash types. Using the new typology would have made the context comparison in step 7 above less neutral. However, as the modified typology only changed the percentage of LTAP/OD crashes in the total crash population from 7.5% to 6.9%, and given the exploratory intent of this study, using context information from the later report was deemed reasonable.

Table 2
Main categories for contributing factors (genotypes) and their observable effects (phenotypes) according to DREAM 2.1.

Genotypes				Phenotypes
Driver		Vehicle	Traffic environment	Timing
Observation	*Cognitive functions*	Temporary HMI problems	Communication	Speed
Interpretation		Permanent HMI problems	Maintenance	Distance
Planning		Vehicle equipment failure	Vehicle design	Direction
Temporary personal factors			Environment design	Force
Permanent personal factors			Experience/training	Object
			Organisation	Duration
				Sequence
				Quantity/volume

to the traffic safety domain of the cognitive reliability and error analysis method (CREAM) (Hollnagel, 1998). DREAM was developed in the FICA project to help provide condensed overviews of crash contributing factors on a case-by-case basis, as well as to facilitate aggregation of case causation data into aggregated causation patterns, or causation charts. It was also used in the project SafetyNet (SafetyNet, 2005; Wallén Warner et al., 2008). For a discussion of how to create and interpret aggregated causation charts using DREAM, see Sandin (2008), Sandin and Ljung (2007) and Wallén Warner and Sandin (2010).

DREAM contains a classification scheme with a large number of factors that can be used to code crash causation information. The scheme distinguishes between observable effects of a control loss in the form of observable effects (called phenotypes) and the contributing factors which bring those effects about (called genotypes). Phenotypes are expressed in the general dimensions of time, space and energy. Genotypes include contributing factors both at the sharp end (close in time/space to the crash) as well as at the blunt end (more distant in time/space, yet important for the development of events). In DREAM version 2.1 which was used here, genotypes are divided into 16 main categories, each belonging to one of three main groups: driver, vehicle and traffic environment. There are also nine different phenotypes (Table 2).

DREAM also includes a link system which specifies possible interactions between contributing factors. When case information on causation is coded into a chart, the link system ensures that the description of how one contributing factor leads to another is not arbitrary. The link system basically limits the range of possible factor interactions to those currently supported by scientific knowledge, thus restricting and guiding the coding of causation information. The inherent structure in the link system also makes it possible to aggregate causation information from multiple case studies in a structured, and principally semi-automated fashion, reducing the number of subjective judgements necessary to identify a pattern of contributing factors for a group of crashes. Naturally, the link system can be updated as new knowledge is gained.

The second step in creating the first abstraction layer was to aggregate the causation charts from the 17 case studies. Here, two things need to be mentioned. First, an underlying assumption of the FICA project is that each driver has his/her own reasons for failing to adapt to the driving situation. Causation information is therefore coded separately for each involved driver. Second, as stated above, vehicle trajectories are a natural frame of reference for ADAS development. There are therefore two aggregated causation charts in the first abstraction layer; one for all left turning drivers (LTAP trajectory) and one for all drivers going straight (OD trajectory).

The aggregated DREAM charts provide a rather complex picture of causation information. While this is useful in detailed discussion of contributing factor patterns, the purpose of the charts in this study was to provide an overview of trends in contributing factor patterns, as well as to make comparison with corresponding charts from questionnaire data possible. The aggregated charts were therefore simplified, by grouping the phenotypes as well as closely related genotypes into the same "box". For example, rather than displaying the three subtypes of *cognitive bias* separately, they were grouped together, and linked to other contributing factors as a single group rather than as separate genotypes. This procedure reduced the number of boxes and links in the original charts, while preserving the main trends in the

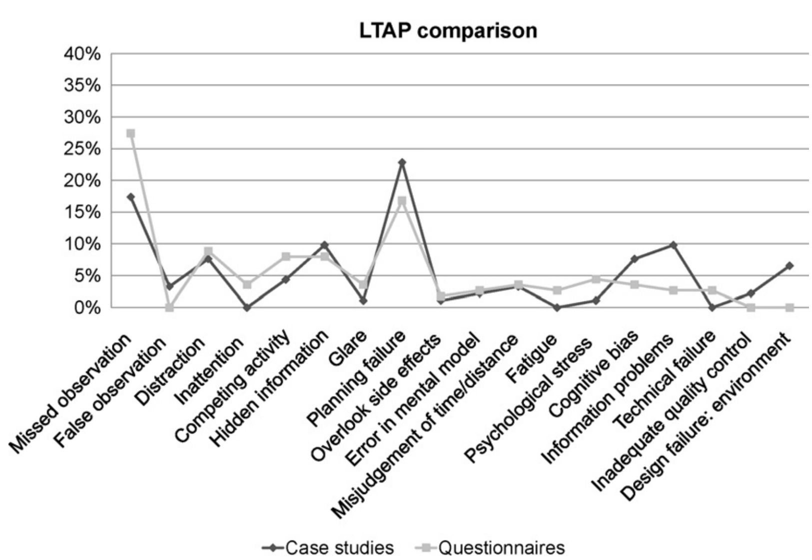

Fig. 3. Comparison of contributing factor frequency for LTAP drivers in case studies and questionnaires. To reduce clutter, factors occurring only once in both first and second layer aggregations have been removed.

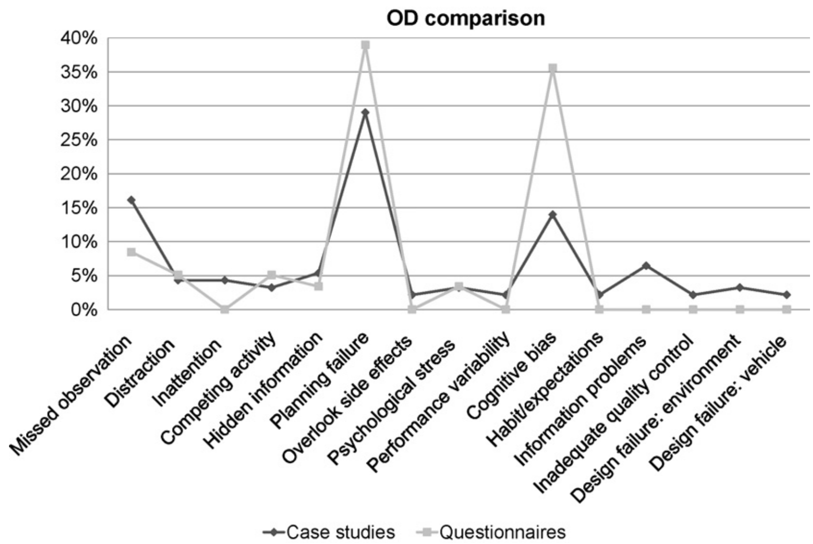

Fig. 4. Comparison of contributing factor frequency for OD drivers in case studies and questionnaires. To reduce clutter, factors which occur only once in both first and second layer aggregations have been removed.

causation patterns. Genotypes belonging to the categories *cognitive bias*, *hidden information*, *planning*, *temporary personal factors* and *experience/training* were grouped, as were all phenotypes (see Table 2).

The analysis of questionnaire data followed the same procedure as the analysis of the case files. Questionnaires matching the LTAP/OD crash type were identified and individually coded using the DREAM method, resulting in a DREAM causation chart for each driver. The individual charts were then compiled into two aggregated charts, one for left turning drivers (LTAP) and one for drivers going straight (OD). The same type of simplifying grouping as described above was performed. The second abstraction layer thus also contains two of causation chart aggregations, one for LTAP drivers and one for OD drivers.

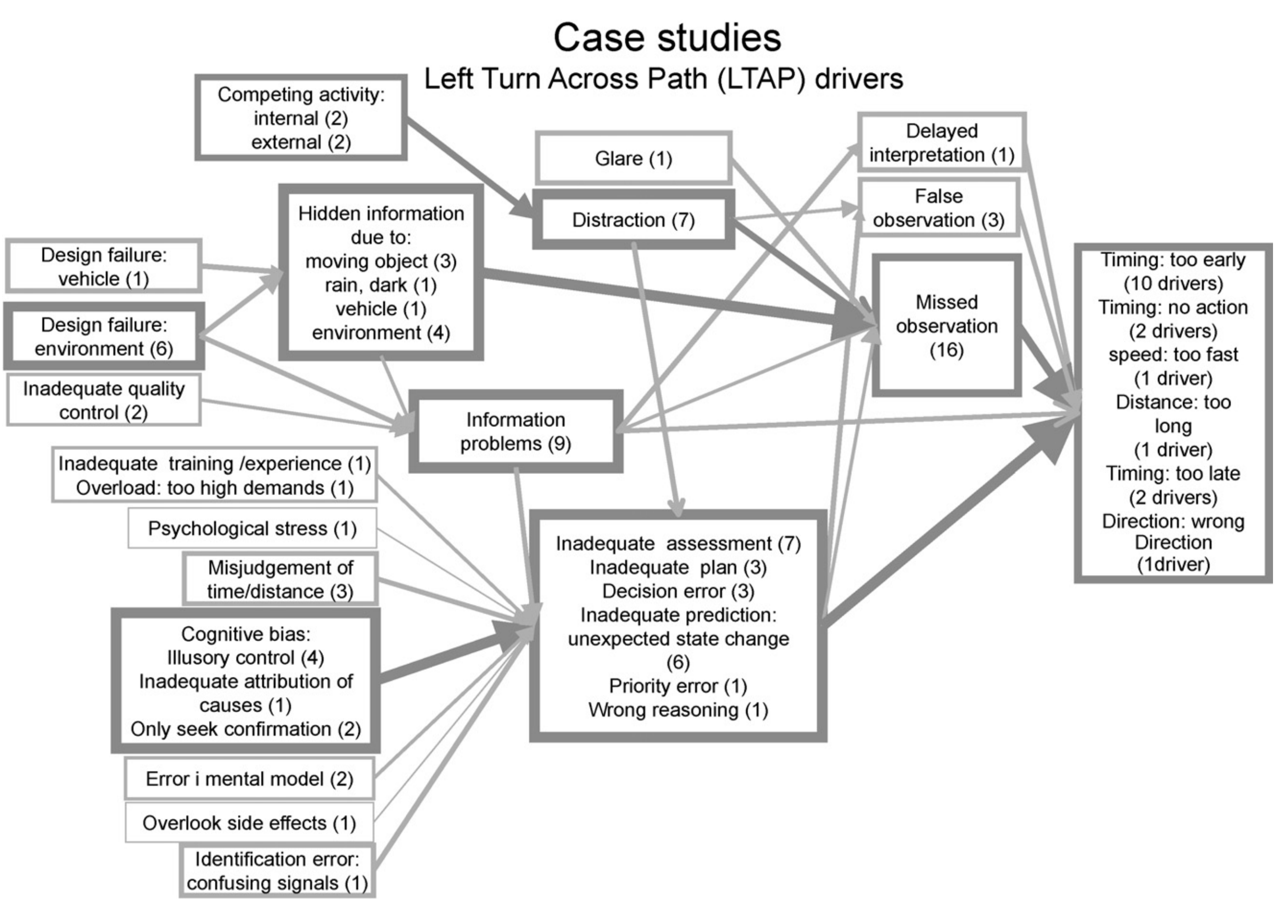

Fig. 5. Aggregated DREAM charts for 17 drivers turning left (LTAP) in case study data.

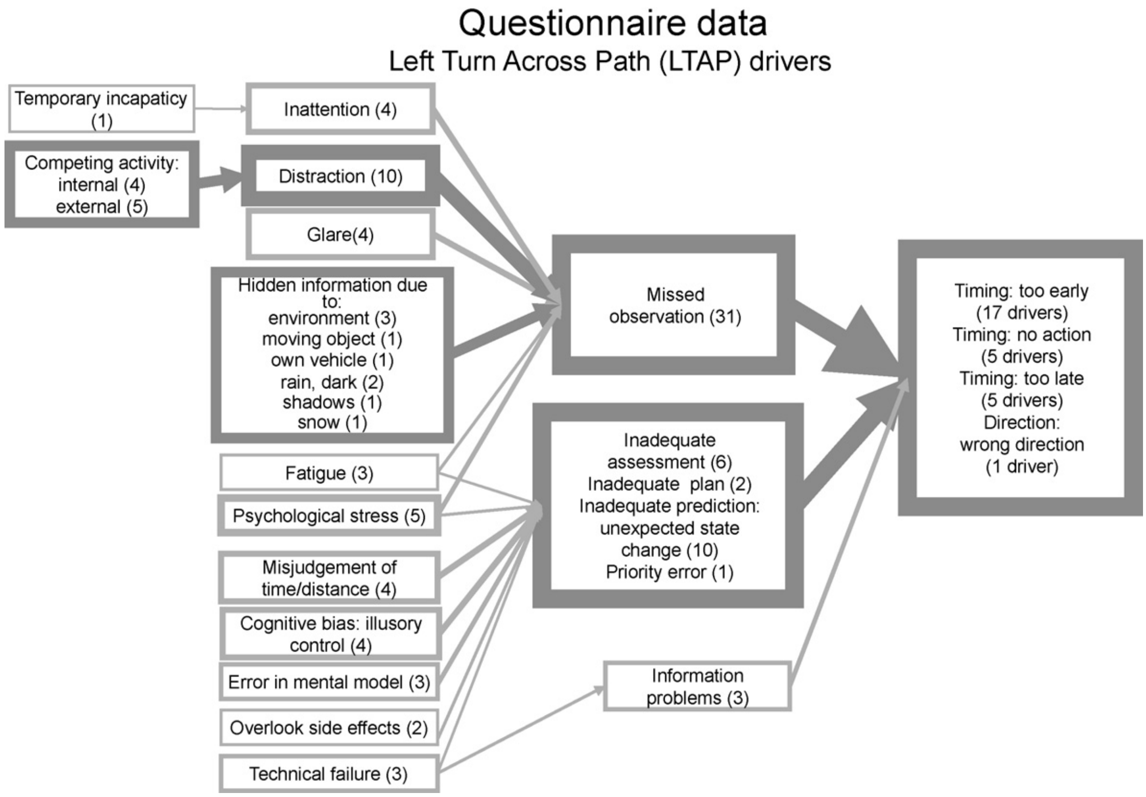

Fig. 6. Aggregated DREAM analysis for 28 drivers turning left (LTAP) in questionnaire data.

3. Results

Here, the patterns of crash contributing factors found in the first and in the second abstraction layers will be presented, followed by the comparison of context variable values in the questionnaire and macroscopic data sets. Note that in the aggregated causation chart in Figs. 5–8, the additional information on what motivates choice of each contributing factor (normally written below the name of the contributing factor in the individual charts) has been removed for readability. However, the analysis is based on the information present in the original DREAM charts.

In the figures below, the total number of times a contributing factor occurs is represented by the number in brackets within each box. Note that DREAM allows attribution of, for example, multiple planning failures or multiple missed observations to a single driver. Some contributing factors can therefore exist in more than one instance per chart, which means their frequency of occurrence can exceed the number of aggregated charts (i.e. the number of drivers). For visual guidance when looking for patterns, the factor frequency numbers are indicated through box border thickness as well. For links between boxes, the number of times a link occurs is not written out, but indirectly represented through the thickness of the connecting arrows.

3.1. *Quantitative comparison of contributing factors in the first and second abstraction layers*

Fig. 3 shows the comparison of contributing factor frequencies for LTAP drivers. The genotypes have been processed as described in Section 2.2.

Fig. 4 shows the comparison of contributing factor frequencies for OD drivers. The genotypes have been processed as described in Section 2.2.

When comparing the pattern of contributing factors in the first and second abstraction layers, Fig. 3 shows that the relative proportions of contributing factors in the first and second abstraction layers is quite similar for LTAP drivers. The in-depth and questionnaire plots follow each other fairly well, with some exceptions (further discussed in Sections 4.2.1 and 4.2.2). Fig. 4 shows the same trend for OD drivers.

A comparison of Figs. 3 and 4 also shows that the overall LTAP and OD causation patters are quite dissimilar. This supports the basic hypothesis underlying the driver based aggregation, which was that drivers on different trajectories experience different types of problems. In the comparison of causation patterns between the case studies and the intermediate layer, LTAP and OD drivers will therefore be discussed separately.

3.2. *Comparing aggregated causation charts from case studies and questionnaires for LTAP drivers*

Fig. 5 shows the aggregated causation charts for left turning drivers (LTAP) in the 17 in-depth case files. Phenotypes and some genotypes are grouped as described in Section 2.2.

Fig. 6 illustrates the result of the aggregated DREAM analysis for the 31 left turning drivers (LTAP) in the questionnaire data. Three LTAP drivers could not be DREAM coded, due to lack of information (see Section 4.1 for a discussion of why). Only 28 drivers are therefore represented in the figure.

From Figs. 5 and 6, it can be determined that there are two main trends for both in-depth and questionnaire LTAP drivers. The first is that a large number of *missed observations* precede the observable failure states (the phenotypes, depicted to the far right in Figs. 5 and 6). *Missed observation* here means that drivers, prior to commencing their turn, have failed to observe the approaching conflict vehicle. The second main pattern is the that there are numerous

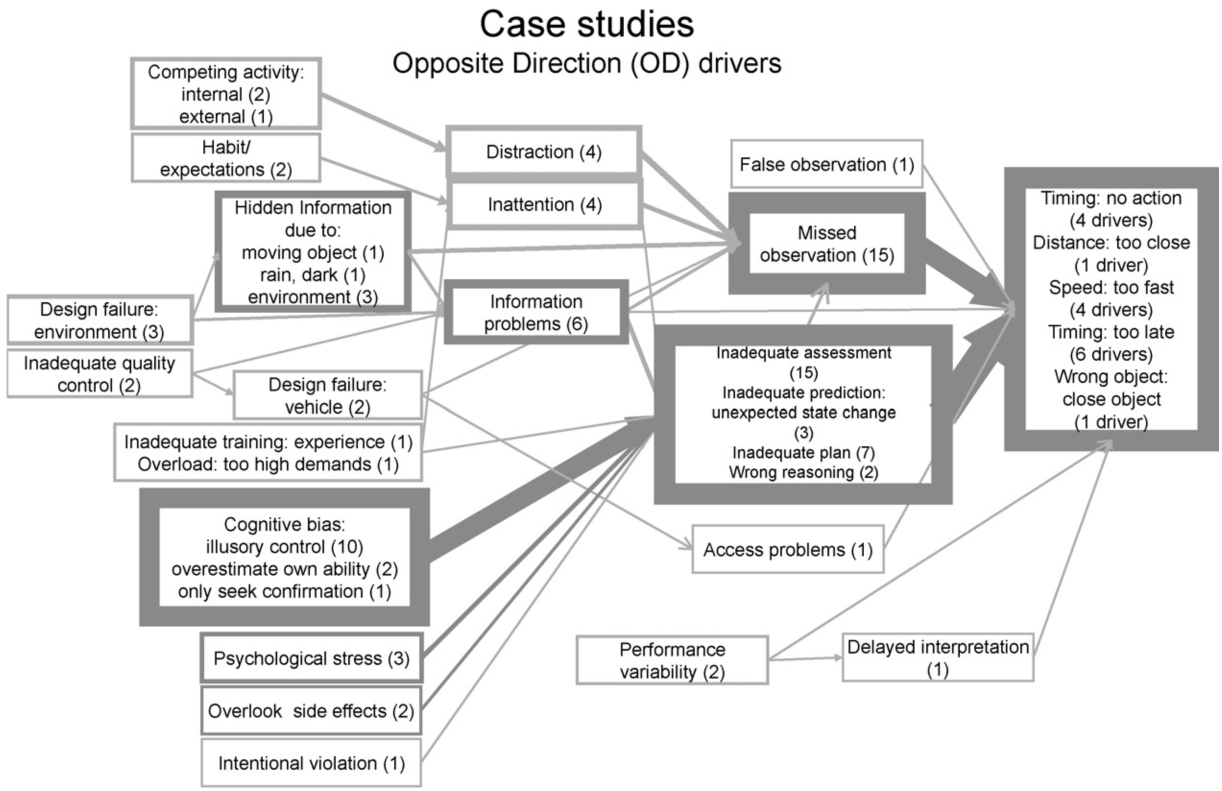

Fig. 7. Aggregated DREAM charts for 16 drivers going straight (OD) in case study data.

instances of planning failures (*inadequate assessment*, etc.), which indicate that drivers understanding of, and adaptation to, the development of events does not match actual events. Also, as frequencies indicate, these factors mainly co-occur, i.e. the crashes occur due to combinations of observation and planning failures.

Regarding the first trend, in the aggregation charts (see Figs. 5 and 6), it can be seen that a main contributing factor to the instances of *missed observation* is *distraction*, often due to a *competing activity* of some kind. Another main contributor is explicit difficulties with lines of sight in the direction of the conflict vehicle, as indicated by the many instances of *hidden information* (information referring to the whereabouts of the conflict vehicle). These contributing factors show fairly equal relative frequencies in the first and second layer charts (Fig. 3). For planning failures, the comparison shows that some of its contributing factors, like *misjudgement of time/distance* and *overlook side effects* have similar relative frequencies in the first and second abstraction layers.

3.3. Comparing aggregated causation charts from case studies and questionnaires for OD drivers

Fig. 7 shows the result of aggregating the causation charts for drivers intending to cross the intersection on a straight path (OD) in the 17 in-depth case files. One OD driver could not be DREAM coded, because the investigators were never able to conduct the driver interview, and there was not enough supplementary crash information to code any contributing factors. Only 16 drivers are therefore represented in Fig. 7.

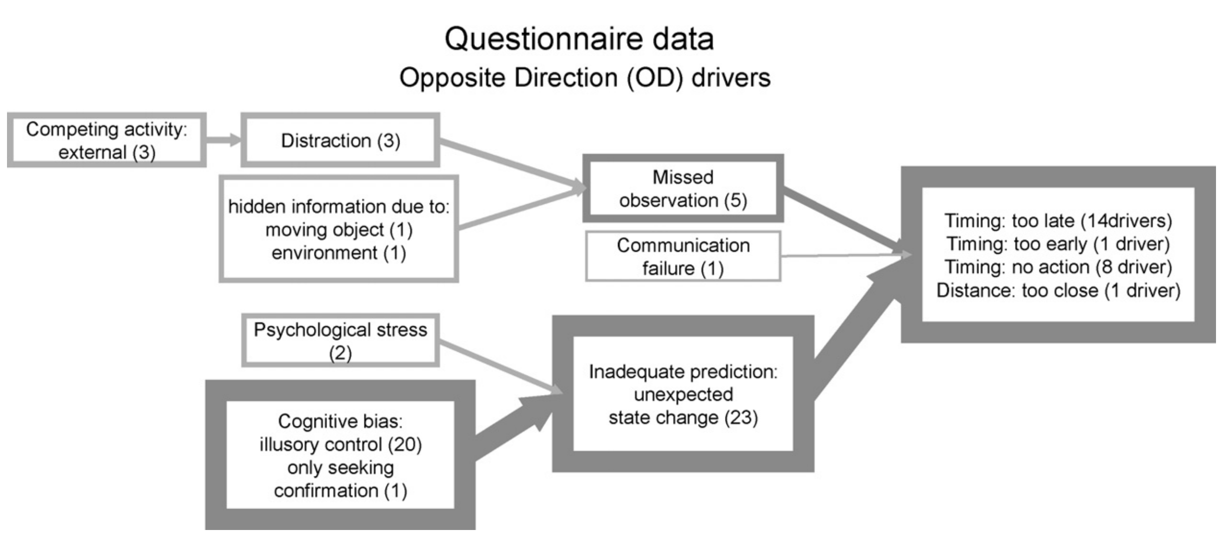

Fig. 8. Aggregated DREAM analysis for 24 drivers going straight (OD) in questionnaire data.

Fig. 8 illustrates the result of the aggregated DREAM analysis for the 26 drivers going straight (OD) in the questionnaire data. Two OD drivers could not be DREAM coded, due to lack of information (see Section 4.1 for a discussion of why). Only 24 drivers are therefore represented in the figure.

For both case study and questionnaire OD drivers, there are two main patterns among the contributing factors. One is that *missed observation* (failure to observe the conflict vehicle) plays an important part. The instances of *missed observations* are mainly due to *distraction* caused by *competing activity*, and *hidden information* (see Figs. 7 and 8) just as they were for LTAP drivers.

A large number of planning related failures are also present for OD drivers. Something which stands out in comparison to LTAP drivers is the high frequency of planning failures due to *cognitive bias*, especially in the questionnaire data. This most likely reflects the fact that OD drivers in the selected case studies more often have the right of way, and the task of identifying and responding to a conflict vehicle therefore usually rests with the LTAP drivers. This assumption is supported by the fact that *hidden information* is more often reported as a contributing factor for LTAP drivers, i.e. because of that responsibility, sight limitations are more debilitating for LTAP driver performance, and hence more likely to be reported as a contributing factor.

3.4. Comparison of context variable values for the questionnaire and macroscopic data sets

In Table 3, a comparison of the six context variables *state of the road*, *weather*, *speed limit*, *light conditions*, *gender* and *age* between Najm et al. (2007) and the 57 LTAP/OD crashes from the questionnaire data is presented. The percentages are based on frequency calculations.

The questionnaires were collected as part of an ongoing statistical study for which crashes are selected based on vehicle make and repair cost criteria (see Section 2.1.3), but no other restrictions apply. The collected questionnaires can therefore be said to represent a random sampling of Volvo car crashes at intersections in Sweden. Comparison on context variables of questionnaire and macroscopic data should therefore show a high degree of similarity, unless underlying cultural and/or geographical artefacts create differences between the crash populations.

From Table 3, it can be inferred that four of the six context variable values for questionnaires and Najm et al. (2007) fulfil this criteria. For *state of the road*, *weather*, *light conditions* and *gender*, values differ only slightly. However for *speed limit* and *age*, there are larger differences. Najm et al. (2007) have a larger share of crashes occurring with young drivers (≤24), and a smaller share of crashes for drivers in the other age groups. The crashes in Najm et al. (2007) also occur at higher posted speed limits.

Table 3
Comparison on context variables for LTAP/OD crashes between Najm et al. (2007) and questionnaire data.

Context variable	Variable values	Questionnaire data	Data from Najm et al.
State of the road	Dry	78%	83%
	Wet/slippery	22%	17%
Weather	Adverse	12%	10%
	Clear	88%	90%
Speed limit (mph)	≤35	67%	37%
	40–45	22%	28%
	≥55	11%	35%
Light conditions	Daylight	69%	62%
	Darkness	19%	31%
	Dusk/dawn	12%	6%
Gender	Male	71%	59%
	Female	29%	41%
Age	≤24	11%	25%
	$24 < x < 64$	73%	65%
	≥65	16%	10%

4. Discussion

The main objective of this study was to describe and test a new methodology for linking causation information from case studies to a macroscopic crash type by means of an intermediate layer of context and causation information. To serve its purpose in an actual study, the intermediate layer (the questionnaire layer) must pass several tests. First, it must contain sufficiently detailed causation information to make a comparison with case study causation patterns possible. Second, that comparison should show similar patterns of contributing factors in the intermediate layer and the case studies. Also, any dissimilarities should preferably be possible to identify as artefacts of data collection rather than dissimilarities of causation. Third, the context of the intermediate layer crashes should be sufficiently similar to the context of the macroscopic crash type. In the following, these three tests will be discussed in turn. Following that, some general issues associated with the proposed methodology will be considered.

4.1. The level of detail in questionnaire causation information

Regarding the level of causation information in the intermediate layer, or second abstraction layer, it can be concluded from Figs. 5–8 that there are overall fewer contributing factors coded for questionnaire drivers than in-depth study drivers. This is not surprising, and follows quite naturally from the fact that a questionnaire captures less data than an in-depth case study, i.e. there will be less information on contributing factors to code. However, the important point is that DREAM coding was possible for almost all questionnaires. Of 57 responses, only five contained insufficient information for creating a DREAM chart.

The most likely explanation for the lack of causation information in those five questionnaires is related to how the questionnaires are administrated. Before receiving the Volvo Cars questionnaire, the crash involved drivers will already have sent in a crash report to their insurance company, Volvia. Those at Volvo Cars who administer the questionnaires report that drivers relatively often call in to ask why they should write down their crash account a second time, having already submitted it once. Due to the name similarity, they believe that Volvia and Volvo Cars are the same company, and think some administrative error must have been made. Though not investigated in particular for the five drivers who failed to submit a crash account in this study, it is reasonable to assume that they belong to the group of drivers who believe that the second request for a crash account is a mistake, and thus they are unwilling to put in the effort required to write it down a second time (they did fill out the rest of the questionnaire after all).

This obviously points to an area of future needs for improvement in data collection procedure for the Volvo Cars questionnaire. In general however, the questionnaires were capable of capturing sufficient causation information to make the analysis of contributing factors possible. The questionnaire data used here thus can be said to pass the first test.

4.2. Causation information in questionnaires compared to case studies

For a number of the contributing factors, the second abstraction layer has a pattern of contributing factors that is similar to those found in the case studies. However, the plots in Figs. 3 and 4 also show some discrepancies. To pass the second test above, these should be possible to identify as artefacts of data collection rather than differences in causation, if the similarity between the two layers shall remain. Whether this is the case is addressed below, with separate discussions for LTAP and OD drivers.

4.2.1. LTAP drivers

One discrepancy is that there are several instances of *inattention* for LTAP questionnaire drivers but none for LTAP case study drivers. *Inattention* here means that drivers fail to perceive the conflict vehicle because they are not paying much attention to the driving task outside of keeping their own vehicle in the lane. This discrepancy is very likely stems from the way crash data is collected. If a driver does not understand why a crash has occurred, there is a certain likelihood that she/he initially will report that she/he must have been inattentive, because she/he cannot think of any other explanation. In questionnaire data, such statements have to be taken at face value. In in-depth investigations however, the investigator can, by control questions and by using information, e.g. from kinematical reconstruction and witnesses, create a deeper understanding of why the crash occurred that involves other contributing factors than *inattention*.

This points to a future need in questionnaire data treatment. If some contributing factors are found to be over- or underreported because there is no in-depth investigator there to ask the driver questions she/he did not think of asking him/herself, some balancing procedure must be developed for the analysis to properly reflect the influence of these factors.

Another discrepancy is that in relation to planning failures, some of the temporary driver related factors (see Table 2) differ between the two LTAP abstraction layers. A major contributing factor in the case studies, which shows a much smaller presence in the questionnaires, is *cognitive bias*. This refers to template based ways of predicting how events will develop which normally function as time and effort saving heuristics in action selection, but which in these cases have lead to conflicts. For example, drivers with the right of way expect any vehicle on a conflicting path to yield and will therefore not put effort into detecting and adapting to such vehicles.

Another factor contributing to the planning failures of LTAP case study drivers which has a much smaller presence for LTAP questionnaire drivers is general difficulties in perceiving information related to intersection negotiation (indicated by *information problems*). Reasons for these difficulties include complex intersection layout, a lack of guidance signs and malfunctioning traffic lights, as indicated by the factors *design failure*: *environment* and *inadequate quality control*. Questionnaire drivers on the other hand have more instances of *fatigue* and *psychological stress* as contributing factors than case study drivers do.

Together, these discrepancies indicate that questionnaire drivers report fewer contributing factors which can be classified as blunt end factors (those more distant in time/space, yet important for the development of events), and more factors which can be classified as sharp end factors (those close in time/space to the crash). A likely explanation for this phenomena parallels the discussion of *inattention* above. In short, crash involved drivers rarely are professional crash investigators. They will therefore not consider the influence of blunt end factors on the event they have experienced, i.e. they may view blunt end factors as part of the circumstances under which the event took place rather than contributing factors in themselves. Since no professional investigator is there to ask control follow up questions on those aspects, information indicating the presence of blunt end factors will be more difficult to capture with questionnaires.

4.2.2. OD drivers

Interestingly, when it comes to *missed observation* due to *inattention*, OD drivers show the opposite pattern of LTAP drivers. There are several instances of *inattention* for case study drivers, but none for questionnaire drivers. Also, OD questionnaire drivers overall do not report any instances of as *misjudgement of time/distance*. A possible explanation for this is related to the fact mentioned above, i.e. that OD drivers in a majority of cases had the right of way. If the LTAP drivers are assigned legal responsibility for the crash, OD drivers may not see a value in identifying further reasons for why the crash took place, unless coached to do so by a professional investigator. Or put differently, while LTAP drivers may feel a sense of responsibility or guilt which drives the effort to explain what happened (to make others understand it was not sheer stupidity), OD drivers may not feel a similar need, since they will not be blamed for the crash. This again brings up the issue of how to control for over- or underreporting of certain contributing factors in questionnaire data.

While OD drivers in the questionnaire data almost solely have *cognitive bias*: *illusory control* coded as contributing to planning failures, OD drivers in the in-depth case studies also have other factors such as *inadequate training/experience*, *overload*: *too high demands* and *overlook side effects* coded as contributing factors. The reason for this is most likely the same as the one for the lack of blunt end factors in questionnaires discussed above. The driver reporting the event is not a professional analyst, and does not think of these factors as possible contributors.

In summary, the analysis of causation pattern similarity in the first and second abstraction layers indicate that the cases analysed in this study pass the second test above. There are clear similarities in causation patterns, and while several dissimilarities also were found, it can be argued that they are more likely to come from the way data has been collected, than from underlying differences in causation.

4.3. Comparing the second layer with macroscopic data on context variables

This leads to the third test above, i.e. the degree of context similarity between questionnaire crashes and the macroscopic crash type. In particular, the possible reasons for the differences in *age* and *speed limit* need to be discussed.

Starting with *age*, a likely reason is the difference in age group proportions of licensed drivers in US and Sweden. For example, in 2007, 13.2% of the licensed drivers in the US were under the age of 25 (FHWA, 2007), while in Sweden this number was only 7.7% (SNRA, 2009). If the VCC crash percentages are weighted to reflect this difference, the original 11% for young VCC drivers rises to 18.2% (see Table 4). This is a large step towards the 24.6% seen in US crashes, and shrinks the original difference between the US and VCC data to a magnitude more in line with the other context variables. The weighting has similar effects on the other age groups as well.

The weighting does not remove the difference entirely however. If it would persist in a future study where larger data samples are used and results are less experimental in character, other explanations would have to be sought. One possibility worth exploring is whether the age distribution for Volvo drivers differs from the Swedish average. For example, because Volvo is considered a premium brand and priced correspondingly, the number of young drivers who can afford a Volvo (and thus who may crash in a Volvo) may be lower then the number of young drivers who can afford a car in general.

The relatively large difference in *speed limit*, indicating that LTAP/OD crashes for Swedish Volvo drivers occur at lower posted speed limits than US LTAP/OD crashes, is cause for concern. The topic of this study is the use of crash data to characterize the

Table 4
Licensed drivers by age group for Sweden and US, original crash involvement for VCC and US, and proportionally adjusted VCC crash involvement.

Age	Proportion of licensed drivers		Original crash involvement		Adjusted crash involvement	
	Sweden	US	VCC	US	VCC	US
≤24	7.7%	13.2%	11.0%	24.6%	18.2%	24.6%
24 < x < 64	71.6%	71.7%	73.0%	65.8%	70.5%	65.8%
≥65	20.7%	15.1%	16.0%	9.6%	11.3%	9.6%

sequence of events which leads to collisions, to use as a basis for setting up ADAS evaluation conditions. Given that ADAS performance is highly dependent on vehicle speeds, a correct characterization of pre-crash scenario speed is very important for the outcome of such evaluations. Possible reasons for this difference are therefore worth discussing at some length.

One possibility is that the difference reflects a real difference in vehicle speeds prior to crashes. A second possibility is that it reflects some cultural or geographical artefact which is irrelevant for pre-crash scenario definitions. For example, if default speed limits on US roads were higher than in Sweden, the US police may on average report higher posted speed limits than Swedish police, regardless of actual vehicle speeds at the crash. A third possibility is that it stems from the sampling criteria. For example, vehicles involved in LTAP/OD crashes may fulfil the questionnaire sampling criteria (a certain repair cost) at lower average speeds than what is necessary to fulfil the macroscopic sampling criteria (a police reported crash with property and/or personal injury).

If the first possibility holds, the implication is that pre-crash scenarios for ADAS evaluation will need country specific adaptation (at least for some variables) in order for evaluation results to be valid. If the second holds, the difference as such can be disregarded, since it will not effect evaluation results. However, other data sources have to be explored to find relevant information on pre-crash vehicle speeds. If the third possibility holds, the implication would be that in order to prevent both questionnaire and police reported crashes, an ADAS would have to be operational for a quite wide range of speeds. It would then be up to the evaluators to decide on if the full range, or just part of it, should be used in the ADAS evaluation.

Which possibility holds cannot be settled from the type of data sources used in this study. Crash investigations rarely have access to onboard vehicle speed recorders, and self-reported driver speeds is not a precise source of information. A valuable complement in this type of analysis would therefore be data collected in naturalistic driving studies and field operational tests, which among other things provides more precise data on vehicle speeds at different locations (see, for example, Dingus et al., 2006; McLaughlin et al., 2008).

4.4. General issues

The focus in the study has been on illustrating the principles and testing the feasibility of the proposed methodology. While this can be said to have been achieved, the results should still be considered highly preliminary, given the small data sets used. In future studies, application of the methodology on a larger data set for both the first and second layer abstractions would be of great importance to gain a further understanding of how far similarities between the layers go, as well as for assessing the robustness of the approach. Also, applying the suggested methodology to more intersection crash subtypes as well as other crash types would help assess its general applicability to the definition of pre-crash scenarios for ADAS evaluation.

A second objective of the study was to try to address the problem of subjective similarity classification in the prototypical scenario approach. Here, the classification scheme and the structure inherent in DREAM's link system did reduce the need for researcher judgement. Basically, while the initial DREAM coding for each case was done by one or more researchers, the need for further subjective judgements in order to identify main contributing factors in each group of cases was removed, since those patterns emerge automatically when the causation charts are aggregated. This is a promising way forward in addressing the subjective judgement problem of the prototypical scenario approach. While it is unlikely that subjective judgement can be fully eliminated at the ground level (analysis of the "raw" data), reducing the number of steps where subjective judgement is needed in further analysis clearly is an improvement.

It should be noted that use of questionnaire data comes with some concerns attached. One is response rates. Even if one follows a sampling plan designed to yield representative data, as long as response rates are below 100 percent there is a risk that particular groups of drivers systematically have refrained from responding. Another concern is that even though the questionnaire was designed to capture causation information, drivers are not professional crash analysts. As the analysis shows, this can lead to under- or over reporting of some contributing factors. Given the limited blunt end factor reporting, further analysis of possible systematical data losses in questionnaire data and means to address them is an important future topic.

Another general issue is that while multiple researchers were involved in the DREAM coding of each in-depth case, all coding of the questionnaires was done by a single researcher (the author). In future studies it would be desirable to have a group of analysts performing the initial coding also for the questionnaire data, to reduce the risk of bias stemming from a particular researcher's point of view. A multiple coder approach does however require that the coding methodology is sufficiently detailed and pedagogical for multiple researchers to used it in an unambiguous and clear way. For the DREAM method used here, a recent study of intercoder reliability and agreement by Wallén Warner and Sandin (2010) indicates that this indeed seems possible.

5. Conclusions

The primary objective of the new methodology proposed here was to address the main problem in developing pre-crash scenarios for ADAS evaluation based on crash data, namely how to establish that causal factors found in microscopic data are representative of a macroscopic crash type, and thus warranted for use in defining the pre-crash scenario. Using a second abstraction layer, as described by the proposed integrated cause and context matching approach, seems a promising way forward. The layer captured information on crash contributing factors in a way which made comparison with selected case studies possible, and it could be created from representatively sampled data which a high degree of similarity to the macroscopic crash type context. While some methodological difficulties were identified, the proposed methodology shows good promise for work related to defining pre-crash scenarios for ADAS evaluation.

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