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Machine and Vehicle Systems

Understanding and prioritizing crash contributing factors

Analyzing naturalistic driving data and self-reported crash data for car safety development

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Cover:
On-board camera views of the road ahead and the driver dialing a phone number (from the EuroFOT-project).

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Abstract

Real world data on driver behavior in normal driving and critical situations are essential for car safety development. Data collection and analysis methods that provide insight into the prevalence of crash contributing factors (e.g., drowsiness, distraction) and causation mechanisms are valuable when making priorities and selecting countermeasure principles.

This thesis investigates different analysis methods applied to real world data from three sources: a crash mail survey, insurance claims, and naturalistic driving. Several analysis methods were investigated, including: adjusting for nonresponse in a crash mail survey, analyzing narratives provided by the involved road users in a crash, and investigating causation mechanisms based on video recordings of critical situations. Naturalistic driving data from whole trips were analyzed to investigate the influence of driving context (e.g., turning, other vehicles, speed) on drivers' eye glance behavior and their exposure to visual-manual phone tasks.

Insurance data proved useful for compensating for survey nonresponse bias related to crash types and driver demographics, while several crash contributing factors are likely to be underestimated in mail surveys due to issues regarding memory and social desirability. Narratives provided detailed additional information explaining why some of the crashes occurred. Video recordings of critical situations consistently revealed contributing factors related to drivers' visual behavior, the road environment, and the behavior of other road users, although drivers' own thoughts and low vigilance were not identified. Naturalistic driving data collected continuously from whole trips were found to be an excellent source of information for studying normal driving behavior. Driving context influenced drivers' eye glance behavior, task timing and overall propensity to engage in visual-manual phone tasks.

In conclusion, no single source of real world data is sufficient on its own to prioritize crash types and contributing factors, and to select countermeasure principles. Future development should emphasize the analysis of large datasets from different sources, in order to provide insights into a wide range of crash contributing factors in different types of critical situations, including severe crashes.

Keywords: Naturalistic driving, mail survey, insurance, nonresponse, narrative, crash, accident, incidents, driving exposure, car safety development.

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List of appended publications

Paper I Tivesten, E., Jonsson, S., Jakobsson, L., & Norin, H. (2012). Nonresponse analysis and adjustment in a mail survey on car accidents. *Accident Analysis & Prevention, 48*, 401-415.

Contribution: The study was designed, analyzed and authored by Tivesten.

Paper II Tivesten, E., & Wiberg, H. (2013). What can the drivers' own description from combined sources provide in an analysis of driver distraction and low vigilance in accident situations? *Accident Analysis & Prevention, 52*, 51-63.

Contribution: The study was designed, analyzed and authored by Tivesten.

Paper III Habibovic, A., Tivesten, E., Uchida, N., Bärgman, J., & Ljung Aust, M. (2013). Driver behavior in car-to-pedestrian incidents: An application of the Driving Reliability and Error Analysis Method (DREAM). *Accident Analysis & Prevention, 50*, 554-565.

Contribution: Tivesten participated in the modification of DREAM, and in the compilation, aggregation, and interpretation of causation charts. Tivesten wrote parts of the paper, and participated in the writing process of the whole paper.

Paper IV Tivesten, E., Dozza, M. (in press). Driving context and visual-manual phone tasks influence glance behavior in naturalistic driving. Accepted for publication in *Transport Research Part F* on the 9^{th} of August 2014.

Contribution: The study was designed, analyzed and authored by Tivesten.

Paper V Tivesten, E., Dozza, M. (submitted). Driving context influences drivers' decisions to engage in a visual-manual phone task: evidence from a naturalistic driving study. Submitted to *Journal of Safety Research*.

Contribution: The study was designed, analyzed and authored by Tivesten.

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List of abbreviations

ADAS	Advanced Driver Assistance Systems
CAN	Controller Area Network
DREAM	Driver Reliability and Error Analysis Method
EDR	Event Data Recorder
FOT	Field Operational Test
NDS	Naturalistic Driving Study
VMC	Vehicle Manufacturer Company

Glossary of terms

Auxiliary variables	Auxiliary variables contain information (e.g., driver age, gender, population for place of residence) on all mail survey recipients and are obtained from a source other than the mail survey questionnaire.
Causation pattern	Shows how several contributing factors are linked together to explain why a crash, near-crash, or incident occurred.
CAN-bus	A CAN-bus monitors and communicates information between different sub-systems in the car (e.g., engine, transmission, airbags), and contains a large number of signals that provide information about the current state of the car (e.g., speed, gear, yaw rate, belt buckle use, steering wheel angle).
Comfort zone	Driving conditions associated with a feeling of control, comfort and safety.
Type of critical situation	The type of movement pattern (trajectory) of the subject car and other involved road users (in relation to the traffic environment) during the critical situation (e.g., car going straight at intersection and pedestrian approaching from left).
Contributing factors	Circumstances that contributed to the crash, near-crash or incident, including factors related to the driver, the vehicle, the road environment, and other road users. The contributing factors can, for instance, be obtained from observation (e.g., video), or interviews with involved road users.
Crash	A collision with an object or other road user, a road departure, and/or a vehicle rollover.
Crash type	Same as *type of critical situation* moments prior to impact.
Critical situation	A situation that results in a safety margin (i.e., distance and time to another road user or object) beyond the driver's comfort zone, used as a collective term for incidents, near-crashes, and crashes.

Discomfort	Due to driving conditions beyond the driver's comfort zone, a feeling of immediate risk or threat in a critical traffic situation, or the mobilization of effort to cope with excessive task demands.
Field Operational Test (FOT)	FOTs use the same data collection procedures as *Naturalistic driving studies (NDS)*, but are designed to evaluate the effect of specific functions in real traffic (e.g., forward collision warning, lane departure warning).
Incident	A situation less severe than a near-crash that reduces the safety margin (i.e., distance and time to another road user or object) beyond the driver's comfort zone.
Insurance claim documents	Includes insurance claim reports from the involved road users, and (in some cases) police reports and written letters from involved road users or witnesses.
Low vigilance	Driver states that include being drowsy, ill, or under the influence of alcohol or drugs.
Mail survey	A pen-and-paper questionnaire sent out by regular mail.
Naturalistic Driving Study (NDS)	Unobtrusive observation of driving in a natural setting for a long period of time (e.g., one year). Vehicles are equipped with sensors, video cameras and data loggers that register information about the vehicle, the driver and the traffic environment.
Near-crash	A situation that could easily result in a crash, that requires a rapid evasive maneuver by one or several involved road users and/or results in a very small safety margin (e.g., distance in time and space) to another road user, object, or a road departure.
Nonresponse (in a mail survey)	Occurs when there were persons in the survey sample who did not respond to the mail survey questionnaire.
Normal driving	Driving characterized by non-critical interactions with other road users and the traffic environment. The driver operates the vehicle without feelings of discomfort.
Observation methods	Methods of data collection that involve on-site or in-vehicle observation, either performed by a person or recorded on video.
Road user	A vehicle driver, pedestrian, or cyclist taking part in traffic.
Safety margin	The distance between two points in a multi-dimensional space, one depicting the current state (of the driver, vehicle, and environment) and the other depicting the closest possible future state at which unrecoverable loss of control would occur (resulting in a road departure or a collision). This distance can, for instance, include variables describing time or physical distance to other road users or objects, friction force (e.g., when negotiating a curve), and the driver state (e.g., attention, vigilance, etc.).
Self-report methods	Methods of data collection that involve asking persons to participate using questionnaires, interviews, focus groups, and driving diaries, etc.

1. Introduction

About 1.3 million people die every year in traffic crashes across the world, and up to 50 million sustain nonfatal injuries (WHO, 2013). The UN has described the current situation as a safety crisis, and in 2010 they proclaimed a "Global Plan for the Decade of Action for Road Safety 2011-2020", encouraging safety development efforts within the whole road transportation system for all countries and regions around the world (UN, 2010). On a national level, the most well-known effort is Vision Zero. Vision Zero was formulated by the Swedish National Road Administration and accepted by the Swedish Parliament in 1997 (Johansson, 2009). Several other countries and organizations have followed this example by adopting similar visions (Corben, Logan, Fanciulli, Farley, & Cameron, 2010; Elvebakk & Steiro, 2009; Eugensson, Ivarsson, Lie, & Tingvall, 2011). Vision Zero states that: “No one shall be killed or seriously injured within the road traffic system.” This statement takes a strong stand; any loss of life or severe personal injury is unacceptable. A prerequisite for such a commitment is that it should not limit the individual needs for mobility, freedom or the growth of society. This is a challenging task that requires efforts within infrastructure, vehicle design, and driver education. Furthermore, a safety perspective that goes beyond injury prevention in collisions is required, since safety while driving must be addressed as well. Real world data constitute a powerful source for safety development that can identify, and provide knowledge about, actual safety problems in real life. It is therefore essential to collect and analyze real world data as an integral part of all safety development.

Car safety is one important component in the development of the road transportation system. From the early 1970s until the end of the 1990s, car safety development was mainly focused on injury prevention in crashes, which has substantially reduced the number of injuries (Isaksson-Hellman & Norin, 2005). As a result, collecting and analyzing data on real world crashes has been used as an integral part of the product development process for many years. More recently, the safety scope has been extended to cover both injury prevention and crash prevention (Eugensson et al., 2011). Thus, there is a need to gain more experience with different methods for collecting and analyzing real world data that support car product development aiming to prevent crashes. For this purpose, real world data needs to provide insights into driver behavior in normal driving, as well as in critical situations such as incidents and crashes.

1.1 Overall aim and scope

The overall aim of this thesis is to investigate the potential of real world data to improve car safety development, by using different data sources and analysis methods in order to understand driver behavior and inform crash-prevention initiatives. Four objectives based on this aim are presented in chapter 5.

To limit the scope, the present thesis focuses mainly on the following aspects:

- The first stage of real world data analysis in the car safety development process, which includes establishing priorities and selecting countermeasure principles. The implications of using these results in the following stages of product development, including verification methods, requirements, and tools (e.g., experiments, computer simulation of driver, vehicle, and environment), are discussed but not specifically studied.
- Some of the existing sources of real word data, including crash mail survey questionnaires, insurance claims, and naturalistic driving studies (i.e., instrumented vehicles collecting data in normal day-to-day driving).
- The ability of different analysis methods to answer the following questions when applied to some existing sources of real world data: (1) How common are different types of contributing factors in critical situations? (2) How do several contributing factors together explain why critical situations occur? (3) How do drivers adapt their exposure and attention to one specific factor (i.e., visual-manual phone tasks) in normal driving?

1.2 Outline

This thesis is organized as follows. A general introduction of the traffic safety problem, along with the overall aim and scope of this thesis, is presented in Chapter 1. This chapter focuses on safety development of the whole road transportation system; car safety is one of several important components. Chapters 2-4 provide a general background related to the scope of this thesis. Car safety development is described in chapter 2, including different types of safety countermeasures and a background on the use of real world data within car product development. Chapter 3 provides a theoretical background on driver behavior as it relates to traffic safety, including models that explain different aspects of normal driving behavior, and why drivers sometimes deviate from normal driving and end up in crashes or other critical situations. Chapter 4 provides an overview of some of the existing methods for collecting and analyzing real world data, with the emphasis on methods that can provide information about driver behavior in normal driving and in critical situations. Based on the introduction and background chapters, Chapter 5 lists the objectives of this thesis. A brief summary of the appended papers and an overview of how they are related to the scope of this thesis are provided in chapter 6. Detailed information is available in the appended papers themselves. The key findings of this thesis are discussed in Chapter 7 in relation to the objectives and the overall aim. General implications for safety development within the whole road transportation system are also discussed based on the results from this thesis. The main findings of this thesis are summarized in Chapter 8.

2. Car safety development

Safety development is a wide area of research that includes road and vehicle design, driver education, and legislation to prevent injuries and crashes. Real world data are essential for this development since they capture real life situations that involve actual vehicles, drivers, occupants, other road users, and the road environment. For car safety development, safe transportation in real traffic is the primary goal (Almqvist, Mellander, & Koch, 1982). This chapter describes a wide safety scope relevant for car safety that covers different phases (e.g., normal driving, critical situations, crashes), and different types of safety countermeasures that are related to these phases. This chapter also provides an overview of how real world data are used within the car product development process.

2.1 What is safety?

Safety covers everything from pre-trip planning, normal driving, to severe crashes. Figure 1 illustrates a driving process relevant for car safety development described by Eugensson et al. (2011).

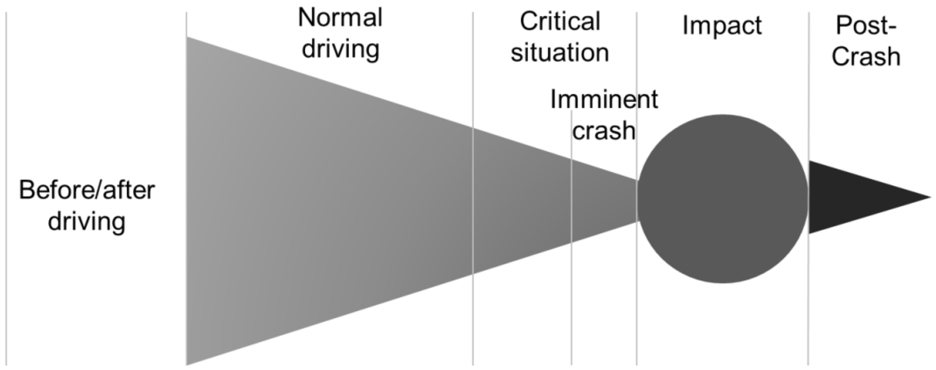

Figure 1: Illustration of a process including the normal driving, critical situation, impact, and post-crash phases relevant for safety development (*adapted from Eugensson et al., 2011).*

The *imminent-crash phase* comprises the moments just before a collision when the crash is unavoidable in most cases, and the *impact phase* includes contact with the collision object and ends when the car is at rest at the crash scene. The *post-crash phase* occurs after impact. Countermeasures protect occupants or other road users from injury based on knowledge about the biomechanics of the human body. During the *imminent-crash phase,* injury prevention countermeasures work by preparing restraints (e.g., pre-crash belt pre-tensioner) and reducing crash energy (e.g., autonomous braking). During the *impact phase* they distribute crash energy (e.g., characteristics of restraints, vehicle structure, and roadside barriers), and in the *post-crash phase* they facilitate the rescue and care of the involved road users (e.g., notifying emergency services personnel).

The vast majority of driving occurs in *normal driving phase,* during which the drivers are in control of the situation and are driving within their preferred safety margins (in terms of speed or distance) in relation to the road, other road users and obstacles (Summala, 2007). *Critical situations* are those in which the drivers deviate from their preferred safety margins (or comfort zone) and want to return to normal driving when they become aware of the situation. Critical situations can be divided into incidents, near-crashes, and crashes, based on their severity (Dingus et. al, 2006).

Countermeasures that prevent crashes are based on knowledge about road user behavior, including how they interact with other road users and the traffic environment. These countermeasures, described in more detail below, can be related to the first three phases on the left side of Figure 1:

- *Before/after driving:* Trip planning (e.g., pre-trip route guidance), driving prevention (e.g., Alco-lock), information on driving conditions (e.g., weather forecast), and measures intended to influence behavioral change over time (e.g., post-drive feedback, education, training, campaigns).
- *Normal driving:* Preventive countermeasures help the driver stay within the *normal driving phase*. Information while driving (e.g., en-route guidance, places to stop, blind spot information), driving performance feedback (e.g., drowsiness alert, distance alert), good visibility (e.g., at intersections, car geometry), general properties of road or vehicle (riding comfort, driving demand, noise, light), and enforcement (e.g., roadside speed controls) are examples of such countermeasures.
- *Critical situations:* There are two principal types of countermeasures that support the driver in critical situations. *Avoidance* systems warn drivers of upcoming situations in time to prevent a crash (e.g., forward collision warning, lane departure warning, rumble strips). *Dynamic* systems improve vehicle performance in critical situations by offering increased brake performance (e.g., emergency brake assist), or improved vehicle stability (e.g., electronic stability control, roll stability control).

This thesis focuses specifically on investigating contributing factors to critical situations, and driver behavior in normal driving.

2.2 Real world data in car safety development

Traditionally, crash investigations have been the main source of real world data used in car safety development aiming to prevent injuries in crashes (Isaksson-Hellman & Norin, 2005). Real world crash data enable a more robust analysis of safety performance and a greater variety of crash situations than can be achieved with crash tests alone. More recently, instrumented vehicles, driven in normal day-to-day conditions, have provided information about normal driving and critical situations (Malta et al., 2012; Victor et al., 2014).

Almqvist et al. (1982) describe a working process for car safety development in which real world data play an important role. First, the data are used to identify the most common crash types and injuries, and a set of safety priorities is formulated for use in strategic decisions. Second, detailed descriptions of the prioritized real world situations and an understanding of the injury and crash causation mechanisms are needed. This knowledge supports the formulation of product requirements for evaluating product performance during different stages of the development process, using physical tests and/or virtual environments (e.g., computer model, driving simulator) that resemble real world situations. Real world data can be used to estimate the safety impact of competing conceptual solutions. For instance, Korner (1989) used real world crash data, laboratory crash data, and injury risk curves to predict the safety impact of changes in car design. More recently, Lindman and Tivesten (2006) used information about the pre-crash phase from real world crashes to estimate the safety impact of an autonomous braking system. Once new car models are on the roads, their safety performance can be validated in real life. Examples of real life validation are studies on the efficiency of electronic stability control (ESC) (Erke, 2008), anti-lock brake systems (ABS) (Evans, 1999), side impact protection systems (SIPS) (Jakobsson, Lindman, Svanberg, & Carlsson, 2010), whiplash protection systems (WHIPS) (Jakobsson & Norin, 2004), and advanced driver assistance systems (ADAS) (Malta et al., 2012).

To assist with crash prevention development, real world data analysis needs to fulfill two goals: (1) Quantify the prevalence of different crash types, crash contributing factors, and their consequences (injuries) in real world crashes. (2) Provide an understanding of crash causation mechanisms.

Crash data must provide sufficient detail, and be representative of all crashes of a specific car model targeted for development, in order to fulfill the first goal (Norin, 2010). These data are essential for a number of reasons: they can reveal existing problems, prioritize them (based on the number of crashes and injuries), and produce results trustworthy enough to be used for strategic decisions. Crash data must be representative because they influence the priorities for safety development, and the estimated real world performance of concepts under development.

Understanding crash causation mechanisms is essential in order to determine which type of countermeasures may be effective. In other words, the countermeasures need to address actual mechanisms in real world crashes. Investigating crash causation mechanisms requires detailed data representative of a specific sub-population and critical situation (e.g., car-to-pedestrian, single vehicle). The data may include not only crashes but also less severe critical situations, such as near-crashes or incidents (Ljung Aust & Engström, 2011; Sandin, 2009). This goal can be divided into several sub-goals, representing different approaches for safety analysis:

a. *Identifying causation mechanisms* that show how several contributing factors together explain why critical situations occur. Examples of investigations of crash causation mechanisms can be found in Sandin (2008).

b. *Detailed scenario descriptions* of the critical (or normal) driving situation, including a description of the road environment, kinematic trajectories of the involved road users, and contributing factors (e.g., driver state, distraction). Scenario descriptions are designed to resemble real life situations and are used for evaluating car and ADAS performance in an experimental setting (e.g. in driving simulators (Ljung Aust, 2010)).
c. *Investigating Driving Exposure* to different driver behaviors in normal driving identifies when, and under what circumstances, drivers engage in different types of behaviors (these findings have implications for d.). For example, roadside observations, naturalistic driving studies, telephone surveys, and mail surveys have been used to measure the extent of mobile phone use while driving (McEvoy & Stevenson, 2008; Young & Regan, 2008).
d. *Estimating crash risk* is based on statistics describing driving exposure (see c.) and crashes (and sometimes near-crashes), for different types of driver behaviors and driver states. Estimating crash risk can include both epidemiological approaches using statistical crash data and naturalistic driving studies including crashes, near-crashes, and a sample of normal driving situations (i.e., baseline epochs) (Dingus, Hanowski, & Klauer, 2011; Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006). These estimates help distinguish between factors that are likely to contribute to crashes (associated with increased risk) and other circumstances (associated with neutral or reduced risk). In addition, crash risk can be used together with driving exposure data (see c.) to estimate the overall safety impact of different driver behaviors.

2.3 Summary

There is a long tradition of using real world crash data in car safety development to prevent injuries in crashes. Crash data are used to prioritize the most common types of crashes and injuries for safety development, and to understand the injury mechanisms. This knowledge is used in the product development process to design car structures and restraint systems that perform well in real life crashes.

In recent years, safety development has been extended to cover both injury and crash prevention. Several countermeasures, including driver support systems, have been introduced to enhance the safety performance of the car and driver in normal driving (e.g., blind spot information) and in critical situations (e.g., forward collision warning, electronic stability control). This extended safety scope creates a need for new methods for analyzing real world data that can be used, in conjunction with existing methods, to establish priorities for crash prevention development and understand crash causation mechanisms. Specifically, the following information will help meet this need:

- Representative crash data (e.g. for all crashes of a specific car model in a specific country) that can reveal the most common crash types and crash contributing factors.
- Detailed descriptions of critical situations (e.g., crashes, incidents) and normal driving, representative of a specific sub-population and/or type of driving situation. These data should reveal how several contributing factors are linked to explain why critical situations occur, in addition to providing specific information (e.g., kinematics of involved road users, driver behaviors, the road environment) about normal and critical driving situations. This allows the estimation of crash risk, driving exposure, and overall safety impact of different behaviors/situations, and the differentiation between contributing factors and other circumstances.

3. Theories on driver behavior related to crash prevention

This section provides a theoretical background for the thesis. Several models that seek to describe and explain normal driving behavior are presented in section 3.1. These models complement each other, as they describe different aspects of the driving task: what the drivers have to do, how they solve the task, and why they solve the task in a certain way (e.g., speed choice, distance) to reach their destination safely and on time. A brief overview of research findings on drivers' visual attention is also presented, since this is an important component of the driving task. Section 3.2 describes the principle for a crash model (commonly referred to as an accident model) that explains why drivers sometimes deviate from normal driving behavior and end up in a crash (or some other critical situation).

3.1 The driving task

Driving is a complex task in which the driver continuously adapts to the road and other road users. Understanding normal driver behavior is essential, not only to support drivers in maintaining control during normal driving, but also to recognize deviations from normal driving. Many theories and driver behavior models have been proposed over the years, as highlighted by Michon (1985). This section provides a brief overview of a few driver behavior models relevant to the present thesis, while more comprehensive reviews are available in the literature (Cacciabue, 2007; Ranney, 1994).

According to Carsten (2007), there are two major types of driver behavior models: *descriptive* and *motivational* models. The most basic descriptive models deal with the driving task itself (or parts of it), i.e., what the driver has to do. More recent descriptive models have been further developed to include control theory, which provides principles explaining how the drivers solve the driving task. Motivational models assume that driving is a self-paced task; drivers select the level of risk they are willing to accept by adjusting their driving behavior (e.g., speed) (Summala, 2007; Ranney, 1994).

3.1.1 Descriptive models

Michon (1985) described driving as a hierarchical task performed at three levels: strategic, tactical, and operational. Each level corresponds to different goals, decisions, and time scales. At the strategic level, the main goal is to arrive safely at a destination on time (Cnossen, Meijman, & Rothengatter, 2004), and the decisions regard general plans, such as route choice. The tactical level relates to the driving situation at hand. The driver has to decide when and where to perform maneuvers (e.g., overtaking, turning, lane changes), and choose the appropriate speed and distance with respect to other road users and obstacles. The operational level involves direct vehicle control (i.e., speed, direction, lane position). High level goals (e.g., time constraints) influence lower level goals (e.g., overtaking), while actual traffic situations influence lower level goals, which can in turn occasionally influence higher level goals. Decisions occur at varying time scales: from minutes to weeks at the strategic level, seconds at the tactical level, and milliseconds at the operational level (Lee, Regan, & Young, 2008; Michon, 1985).

Several researchers (Hollnagel, Nåbo, & Lau, 2003; Hollnagel & Woods, 2005; Lee et al., 2008) have combined basic descriptive models with control theory. Hollnagel and Woods (2005) defined control as "*The ability to direct and manage the development of events, and especially to compensate for disturbances and disruptions in a timely and effective manner*". In driving, control is not considered for the driver alone, but for the driver and vehicle as a joint system (Hollnagel et al., 2003). Control theory is based on the principle that there is a goal state, or a target value, that the system maintains or strives towards. Lee et al. (2008) describe driving as a task that contains goals and control processes at each of the task levels described by Michon (1985). Lee et al. (2008) propose that drivers use three types of control: *feedback*, *feedforward*, and *adaptation*. Drivers respond to differences between the selected goal state and the current driving situation using feedback control. Drivers also act based on how they anticipate the situation will develop using feedforward control (i.e., based on predicted deviations from goal state). Finally, drivers adjust their goal state using adaptive control, which can be described as a form of meta-control that compensates for changes in demands from driving and other tasks (Lee et al., 2008).

Engaging in secondary tasks while driving (e.g., eating, reading, talking with passengers) has been widely acknowledged as a major safety concern (Craft & Preslopsky, 2009; Klauer et al., 2006; Olson, Hanowski, Hickman, & Bocanegra, 2009; Stutts & Hunter, 2003). Descriptive models have been applied to describe secondary task engagement while driving (Lee et al., 2008; Schömig & Metz, 2013). At the strategic level, drivers decide under what circumstances they consider it appropriate to engage in secondary tasks. Strategic decisions include specific strategies, such as bringing a phone into the car with the intention to make a call, and general strategies, such as only making the call in situations perceived as less risky (e.g., while standing still in traffic). At the tactical level, the driver decides on the timing of the task, and whether to engage in it based on the current and anticipated development of the traffic situation. At the operational level, the driver distributes his/her attention between driving and performing the secondary task.

3.1.2 Motivational models

Motivational models assume that driving is a self-paced task in which drivers choose the level of risk that they are willing to accept (Ranney, 1994). For instance, the zero-risk theory assumes that as drivers adapt to changes in the road environment they strive to maintain a state where, by their estimation, there is no risk of a crash (Summala, 1988). Based on the work by Damasio (1994) and Vaa (2007), Summala (2007) propose an updated model replacing risk with discomfort, in which safety margin is the primary control measure. Safety margin can be described as the available distance in time and space (or available friction) between the current conditions and those under which a crash is unavoidable. Drivers' time goals and motives, such as maintaining speed and the pleasure of driving, act as constraints to push drivers towards shorter safety margins. At the same time, drivers strive to avoid feeling the discomfort associated with too small safety margins. Drivers can compensate for task difficulty by modifying their effort (e.g., vigilance, attention) or by adjusting the task itself (e.g., reducing speed). In addition to a cognitive component, estimation of safety margins has an affective component that facilitates and speeds up drivers' choices. A feeling of comfort is associated with normal driving, while drivers experience discomfort when they become aware of a critical situation (i.e., incident or near-crash). The motivational model can be linked to the phases in Figure 1, which are addressed by different types of driver support systems as described by Ljung Aust and Engström (2011).

3.1.3 Visual attention in driving

The driving task relies heavily on visual input (Sivak, 1998), since most of the information needed for driving is visually available in the environment, in contrast to other complex dynamic tasks such as air traffic control (Cnossen, 2000). Studying drivers' visual behavior is therefore highly relevant for traffic safety research since it provides insights into drivers' visual attention mechanisms.

Experienced drivers know where and when to look for information in the traffic environment, based on experience with similar situations. Drivers also rely on properties like movement, contrast, and object size to detect more unexpected changes in the traffic environment (Engström, Victor & Markkula, 2013). The human visual system can extract detailed information using foveal vision (in the gaze direction), while peripheral vision is sensitive to movement but cannot capture detailed information. Consequently, drivers constantly shift their gaze to different areas of the traffic environment to obtain an overview of the traffic situation. Several researchers have demonstrated that experienced drivers use peripheral vision and the near-road area to control the lateral position of the vehicle (Land & Horwood, 1995; Mourant & Rockwell, 1970; Summala, Nieminen, & Punto, 1996). In driving (and other everyday tasks) eye fixations precede actions. For instance, drivers make anticipatory fixations before entering a curve in order to estimate curvature and look for potential threats, such as oncoming vehicles (Land & Lee, 1994; Lappi, Lehtonen, Pekkanen, & Itkonen, 2013; Lehtonen, Lappi, & Summala, 2012). The presence of other vehicles (e.g., lead vehicle, oncoming vehicle) influences drivers' glance behavior in normal attentive driving (Olson, Battle, & Aoki, 1989; Serafin, 1994). For example, in car-following, drivers tend to look away from the road only when speed and distance to the lead vehicle are close to constant (Tijerina, Barickman & Mazzae, 2004).

Secondary task engagement also influences drivers' visual behavior. Drivers tend to concentrate their gaze on a smaller area of the road ahead while engaging in cognitive tasks (e.g., problem solving) (Victor, Harbluk, & Engström, 2005), and use a time-sharing strategy when engaged in visually demanding tasks (e.g., entering a navigation destination). Wierwille (1993a, 1993b) described this time-sharing strategy in a model in which drivers constantly look back and forth between the road and the secondary task. Wierwille's model assumes that looking away from the road for 1 second is perceived as unproblematic, while drivers avoid looking away for more than 1.5 seconds. Previous studies have found that although different in-vehicle tasks vary only slightly for mean off-road glance durations, they vary considerably for the total number of glances required to complete the task (Dingus, Hulse, Antin & Wierwille, 1989; Wierwille, 1993b).

3.2 Crash models

All crash investigations have an underlying model (formalized or implicit) that influences both the data collection and the factors that are identified as contributing factors (Leveson, 2004). Such a model describes the principles regarding how and why crashes occur. It specifies contributing factors (i.e., possible causes) and the links between contributing factors and their consequences (Huang, 2007). Models that describe crash causation mechanisms can be categorized as sequential models, epidemiological models, or systemic models (Hollnagel, 2004; Huang, 2007). Systemic models are the most appropriate type for describing accidents in highly complex systems (Hollnagel, 2004; Leveson 2004) such as road crashes. Systemic models describe complex interactions of contributing factors and events (Huang, 2007), and consider the driver and vehicle as a joint system (Hollnagel et al., 2003). The Driver Reliability and Error Analysis Method (DREAM) (Ljung, 2002; Wallén Warner, Björklund, Johansson, Ljung Aust, & Sandin, 2008), based on a systemic accident model, is further described in section 4.1.2.

3.3 Summary

There is not a single theory or model on driver behavior that fully covers the scope of safety described in section 2.1. Instead, the models presented in this chapter capture different aspects of the driving task in normal driving and in critical situations such as crashes, which is useful when designing different types of countermeasures.

Driving is a dynamic and complex task that relies heavily on visual input, and includes interdependent goals and decisions that occur at different time scales. Drivers use different control strategies to manage the demand from driving and other tasks. These strategies include responding to current and anticipated changes in the road environment as well as adapting their driving (e.g., speed, distance to lead vehicle, distribution of attention) to changes in the demand of driving and other tasks. Time constraints and other motives push drivers towards shorter safety margins (e.g., distance to other vehicles, speed choice), while drivers maintain sufficient safety margins to avoid feelings of discomfort. Crashes and other critical driving situations are best described by a systemic model that can incorporate the complex interactions of several contributing factors.

4. Methods to collect and analyze real world data on driver behavior

Within road safety research, real world data collection relies largely on self-report methods or observation methods. Self-report methods include questionnaires, interviews, focus groups, and driving diaries (Lajunen & Özkan, 2011). Observation methods record driver behavior and/or interactions between road users (Hydén, 1987; Dingus et al., 2006), by means of video cameras or manual observers at the roadside, or video recordings in vehicles. These methods can be complemented with physical on-scene or in-vehicle measurements (e.g., speed, acceleration, distance) obtained from sensors, manual measurements, or video image processing. Overall, there are many available methods for collecting real world data on driver behavior. A few methods of special interest for car safety development are further described below.

4.1 Retrospective crash investigations

Most crash data are obtained in retrospective investigations, meaning that the data are collected after the crash occurred. Crash data from in-depth investigations, police reports, insurance claims and mail surveys rely largely on self-report methods, such as interviews and questionnaires. Information is provided by the involved road users and their recollection of the event is therefore crucial. However, there are known limitations to the accuracy of event memory. Eyewitness memory is influenced by the perception of the original event, the retention of memory, and the retrieval of memory when asked about the event (Loftus, 1979). This means that a person's memory may be modified after the crash occurred, or influenced by question wording when asked about the event (Loftus, 1979). Furthermore, according to Lajunen and Özkan (2011), drivers are unaware of most basic motor and perceptual processes that quickly become automated when learning to drive. Thus driver behavior that is over-learned may be inaccessible in self-report methods such as interviews (Clarke, Forsyth, & Wright, 1998).

An additional source of bias in self-reported data is social desirability (af Wåhlberg, Dorn, & Kline, 2010; Lajunen & Özkan, 2011), which can be described as "*a tendency to give answers that make the respondent look good*" (Lajunen & Özkan, 2011). Social desirability consists of two components, impression management (lying) and self-deception, that need to be considered when using self-reports of driver behavior. Impression management tends to increase in public compared to anonymous settings, while self-deception is more linked to personality (Lajunen & Özkan, 2011).

4.1.1 Police reports

Police-reported crashes are the most widely used and accessible form of crash data in large datasets. Police-reported crash data usually include almost all fatal crashes, and most crashes resulting in severe personal injuries, from an entire country. Crashes with less severe personal injuries are, on the other hand, less frequently reported (Elvik & Mysen, 1999). These investigations primarily focus on legal liability, which can make the involved road users reluctant to provide information that can be incriminating (Shinar, Treat, & McDonald, 1983). Consequently, there is usually limited information about the pre-crash phase (including crash contributing factors) in police-reported crashes.

4.1.2 Crash mail surveys

Mail surveys can be used to collect crash data (Sagberg, 1999, 2001) or more general driving behavior (Reason, Manstead, Stradling, Baxter, & Campbell, 1990). The strength of mail surveys is that a broad range of questions can be asked, and they can reach many persons over a wide geographical area at a low cost (Dillman, 1991). Their limitation is that several potential sources of survey error need to be addressed before the data are used for statistical analysis.

According to Dillman (1991), there are four types of survey error: sampling error, noncoverage error, nonresponse error and measurement error. The first two are related to the sampling procedure: the number of selected units (e.g., persons), and whether the sampling frame covers the study population.

The third type, nonresponse error, occurs if the survey respondents differ systematically from the nonrespondents in a way that is important to what the survey is measuring. Response rates have declined for mail surveys in developed countries over the last decades, leading to a growing concern over nonresponse error (de Leeuw & de Heer, 2002). While the most common advice for dealing with nonresponse bias is to increase response rates, recent research suggests that there is no clear relationship between response rate and nonresponse bias (Groves, 2006; Olson, 2006). Instead, nonresponse bias occurs as a function of how correlated the survey variables are to response propensity (Groves, 2006). Analyzing nonresponse, and if necessary adjusting for nonresponse bias, is therefore essential for survey research, even if response rates are fairly high. Nonresponse analysis and adjustment are well established for mail survey research in general, but are not commonly performed when using mail surveys to collect crash data.

Finally, measurement error is related to how the respondents interpret and respond to the questions in the survey. Measurement error can be the result of poor questionnaire design or wording (Dillman, 2007). Other sources of measurement error are related to what the respondent is willing to report and able to recall correctly. Mail survey questionnaires that promise anonymity favor less socially desirable responses (Lajunen & Summala, 2003). It is, however, difficult to assess the influence of social desirability and recall bias without having access to other sources of information. Lajunen and Özkan (2011) suggest emphasizing anonymity in mail surveys, as well as including addition scales (e.g., social desirability) and objective measures (e.g., observations of crashes and driver behavior) to balance against social desirability response bias.

4.1.3 Insurance data

Insurance data provide another source for crash statistics. Insurance companies gather insurance claim reports of the involved road users and witnesses, and code information about the involved road users, the vehicles and any personal injuries into the company database. Compared to police data, insurance data can cover a broader spectrum of crashes, including damage-only crashes (Hutchingson, 1987; Daniels, Brijs, & Keunen, 2010), and provide more precise information about the vehicles involved (Hutchingson, 1987). These data also provide general information on a large number of crashes that are representative for all insured vehicles. The insurance data are, however, collected some time after the accident occurred and focus on liability for payment, which may limit the information available (Hutchingson, 1987).

4.1.4 In-depth crash investigations

In-depth investigations can provide more detailed information about the pre-crash, crash and post-crash phases than is available in official crash databases that relies on police reports. Larsen (2004) described in-depth investigations performed by a multidisciplinary team that visited the scene shortly after the crash. The team collected data through interviews of the involved road users and witnesses, as well as inspecting the road environment and the involved vehicles. In-depth investigations can provide information on why the crash occurred that is difficult to obtain from other sources of crash data, such as police reports (Grayson & Hakkert, 1987). Interviews that take place on-scene shortly after the crash may have some advantages over interviews conducted later, in terms of completeness and accuracy of the road users' statements. Limitations in perception, recollection of the event and social desirability, on the other hand, cannot be ruled out. Further, these investigations are costly and usually cover only a few cases, with an unclear representation of the study population (Grayson & Hakkert, 1987). Databases such as the German In-Depth Accident Study (GIDAS) address some of these issues. Their investigation teams are available at any hour of the day or night, performing approximately 2000 in-depth investigations each year and covering two geographical areas, making the investigations fairly representative of all injury crashes in Germany (Otte, Krettek, Brunner, & Zwipp, 2003; Otte, Jänsch, & Haasper, 2012).

In-depth investigations are valuable when analyzing crash causation mechanisms because they can provide detailed information about contributing factors and their interactions that is difficult to obtain from traditional crash data (e.g., police reports) (Grayson & Hakkert, 1987). Classification of crash causation is specifically addressed with methods such as the Driver Reliability and Error Analysis Method (DREAM)

(Ljung, 2002; Wallén Warner et al., 2008). This method analyzes contributing factors related to the road users, the vehicles and the environment according to a systemic accident model. These factors can be present shortly before the collision (e.g., late observation of the critical situation, misjudgment of time gaps) or long before the crash occurred (e.g., inadequate vehicle maintenance, time pressure) (Wallén Warner et al., 2008). Thus DREAM allows a systematic classification of critical events, contribution factors, and links to causation patterns. A similar classification of safety-critical situations, such as near-crashes and incidents, can be obtained from naturalistic driving data by analyzing them in the same way as crashes (Engström, Werneke, Bärgman, Nguyen, & Cook, 2013).

4.2 Observational studies

4.2.1 On-site observation

On-site observation methods use either on-site observers or video cameras to record information on traffic and/or drivers at a specific location.

The traffic conflict technique (TCT) was developed to evaluate traffic safety for specific locations (e.g., intersections) (Grayson, Hydén, Kraay, Muhlrad, & Oppe, 1984; Kraay & van den Horst, 1985; Perkins & Harris, 1968). The TCT analyzes the interactions between different road users, and organizes interactions into a safety hierarchy of event severity, ranging from normal interactions to serious conflicts, including crashes and near-crashes (Hydén, 1987). Crashes are rare and unpredictable events that are difficult to observe as they happen. Early research in TCT used serious conflicts as surrogates for crashes to overcome these limitations and to better estimate the predicted number of crashes. More recent research has analyzed the shape of hierarchies (i.e., distribution of event severity) as an indication of a location's safety (Svensson, 1998). This type of analysis can provide some insights into drivers' preferred safety margins in different types of interactions (e.g., when turning left across the path of oncoming vehicles, red light stop/go decisions). However, information on contributing factors that relate to driver behavior in critical situations is limited.

There are other types of roadside observations that more specifically focus on investigating seatbelt usage or the exposure to driver distraction in normal driving. For instance, the National Occupant Protection Use Survey (NOPUS) performs on-site observation to record drivers using electronic devices in a representative sample of intersections in the United States (NHTSA, 2014). The survey is performed in the same way every year, allowing for a trend analysis on drivers' electronic device use. Visual-manual tasks involving electronic devices appear to have increased from 0.2% to 1.5% of the observed drivers during the time period 2005-2012. Only vehicles stopped at intersections during daylight were observed, restricting the data collection to one low-demand driving situation. Furthermore, on-site observation is not a suitable method for recording hands-free phone use, since, for example, it is difficult to know if the driver is talking on the phone or with a passenger (McEvoy & Stevenson, 2008). Photographs taken of drivers in passing vehicles on high-speed roadways have also been analyzed, in order to measure the prevalence of various distracting activities (Johnson, Voas, Lacey, McKnight, & Lange, 2004). This study estimated a lower prevalence of mobile phone use than the NOPUS study did.

4.2.2 Naturalistic driving studies (NDS)

Naturalistic driving studies (NDS) collect driving data from vehicles driven in real traffic for normal, everyday purposes. In the 100-car naturalistic driving study (100-car study), the first extensive NDS, 100 cars were driven in real traffic for one year (Dingus et al., 2006). In NDS, the vehicles are equipped with sensors and video cameras. An NDS can collect data continuously during whole trips, as was the case in the 100-car study, or only during specific events, triggered by, for instance, medium to hard braking (Uchida, Kawakoshi, Tagawa, & Mochida, 2010). NDS data usually contain video recordings of the driver and the traffic environment, as well as a large number of time-history measurements (e.g., speed, acceleration, steering wheel angle). A similar data collection approach is used for evaluations of ADAS, which is referred to as a Field Operational Test (FOT) (Victor et al., 2010). The strength of NDS/FOT is that they can provide high-resolution information about the traffic situation and road user behavior in real traffic (Klauer, Perez, & McClafferty, 2011). The main limitation with these studies is that they generally include only a small number of drivers from a specific geographical region, so it is unclear how well they represent all drivers within that region. Also, near-crashes are combined with crashes to evaluate the level of safety risk associated with different behaviors, since the number of recorded crashes is limited. Most crashes are also low-severity impacts with a high proportion of lead vehicle crashes. Their distribution does not resemble the distribution of the types of critical situations present in injury crashes. For instance, the 100-car study contained 12 police-reported crashes, 69 crashes in total, and 761 near-crashes (Dingus et al., 2006). About half of the crashes and near-crashes involved a lead vehicle. Large EDR/NDS datasets can provide more data on critical situations which are both relatively rare and associated with a high injury risk in case of a crash (e.g., oncoming vehicle, run-off-road). The Strategic Highway Research Program 2 (SHRP2) project addresses this issue by instrumenting 2800 cars across 6 sites in the U.S., and recruits drivers from different age groups, genders, socioeconomic strata, and types of cars that represent the driver population in the U.S. (TRB, 2013).

The continuous data collection of NDS from whole trips offers new opportunities to study driver behavior in normal driving and critical situations, and to estimate crash/near-crash risk associated with different driver behaviors. A case-control design is commonly used In NDS studies, where odds ratios are used as an approximation of relative risk (Klauer et al., 2011). In the 100-car study, odds ratios were computed by comparing crashes and near-crashes (cases) with a random selection of 6-second baseline epochs (controls) (Klauer et al., 2006). The reason for combining crashes and near-crashes is that the relatively small number of crashes does not allow for precise risk estimates. Guo, Klauer, McGill, and Dingus (2010) recently concluded that there is a strong relationship between crashes and near-crashes in the frequencies of contributing factors. They also concluded that risk estimates consistently underestimate the crash risk of contributing factors when near-crashes are included.

Data from NDS have been analyzed to estimate crash risk associated with different types of secondary tasks (e.g., reaching for a moving object, sending a text message, using a calculator), driver metrics (e.g., eye glance behavior), and driver states (e.g., drowsiness) (Klauer et al., 2006; Liang, Lee, & Yekhshatyan, 2012; Olson et al., 2009). Klauer et al. (2006) found that severe drowsiness and complex visual-manual tasks were each associated with an increased risk of crash involvement. Secondary tasks are considered complex tasks when they require several manual inputs and glances away from the road. Another finding from the 100-car study was that looking away from the road for more than 2 seconds (during one or more glances) in a 6-second window was associated with an increased risk (Klauer et al., 2006). Further analysis of the 100-car data has revealed that single off-road glance duration is a more powerful predictor of crash risk than glance history or glance location (Liang et al., 2012).

The safety impact of different driver behaviors (e.g., visual-manual tasks) depends on several factors. These include how often and under what circumstances drivers decide to engage in the behaviors (i.e., exposure) and the crash risk once they are engaged in that behavior (Young & Regan, 2008). Drivers' risk adaptation and state, along with the circumstances under which they engage in certain behaviors, also influence the exposure and safety impact (Dingus et al., 2011).

Another potential application for NDS, rarely explored in the literature, is extracting detailed information about normal driving behavior from the huge amounts of data available.

4.3 Self-report methods investigating drivers' exposure and decision to engage in secondary tasks

Self-report methods such as mail surveys and telephone interviews are frequently used to estimate the prevalence of driver distraction and its patterns of exposure (Young & Regan, 2008). For instance, these surveys may provide information about the frequency of phone use: in general terms, whether drivers occasionally or never use their phone while driving. The surveys can also ask about more specific types of phone use, such as whether drivers use a handsfree device, or if they send text messages while driving. These questions can reveal information about specific groups of drivers, such as which are more likely to engage in distracting activities, and what their attitudes are towards different behaviors (McEvoy & Stevensson, 2008). Lerner, Singer and Huey (2008) used focus groups to investigate the role of motivational factors (e.g., social, economic, lifestyle) in the use of in-vehicle devices, as part of an investigation into the strategies used to decide to engage in distracting tasks while driving. They found that the motivational factors were more important than roadway and task demands; furthermore, teen drivers were much more willing to engage in distracting activities and enjoyed the challenge of multitasking more than mature drivers.

4.4 Summary

Police-reported crash data, mail surveys, and insurance data are the most common sources for crash statistics. Police-reported crashes are usually representative of all fatal crashes in a country, while insurance data are more comprehensive, covering a wider range of crash severities, including damage-only crashes. Mail surveys can be sent to a large number of crash-involved drivers, but low response rates raise the question of how representative the obtained crash data are. These data sources all rely mainly on self-reports, which are vulnerable to biases of recall and social desirability. In addition, police reports and insurance records focus on legal or financial liability, which limits the information provided. Crash mail surveys provide the opportunity to ask any questions related to crash contributing factors, but the influence of bias due to nonresponse, social desirability, and memory is not well understood.

In-depth crash investigations and naturalistic driving studies (NDS) can provide data that are representative for a sub-population of drivers, and one or several geographical regions. In-depth crash investigations collect detailed data to investigate the contributing factors and crash causation patterns associated with different crash types. Naturalistic driving studies (NDS) provide detailed information about the driver, vehicle, and road environment, albeit for a limited number of drivers. NDS data collected continuously during whole trips allow the study of both driving exposure and contributing factors to critical situations, which makes it possible to estimate the crash/near-crash risk and overall safety impact of different driver behaviors. NDS studies generally provide a large amount of data for normal driving, a smaller amount for crashes, and even less for severe crashes. In contrast, event-triggered NDS is a cost-effective method for recording data and studying contributing factors in critical situations, but it lacks information about driving exposure. In-depth investigations rely partly on self-reports, and NDS relies on in-vehicle observations. These differences in the data collection approach are likely to influence which crash contributing factors are captured with each method.

On-site observation, mail surveys, and focus groups are useful for studying general attitudes, different strategies to manage risks, and common behaviors in traffic. These methods can measure changes in (for instance) exposure to mobile phone use while driving. On-site observations are limited to one specific location and driving condition (e.g., standstill at intersection), while focus groups and questionnaires pose more general questions about different behaviors that cannot be directly linked to crash data.

5. Objectives

Based on the overall aim and scope of this thesis (stated in section 1.1), the objectives in this thesis are to:

1. Investigate an existing method for analyzing, and compensating for, the influence of nonresponse bias in a mail survey applied to car crashes, using auxiliary data from an insurance company. The method is investigated to determine the influence of nonresponse weighting in estimating the prevalence of crash contributing factors related to driver behavior (e.g., low vigilance, driver distraction), and to identify the most influential weighting variables (Paper I).

2. Examine the additional value of analyzing narrative from a crash mail survey and insurance claims, compared to using mail survey variables alone, in improving the estimated prevalence and provide more specific information on crash contributing factors related to driver behavior. (Paper II).

3. Investigate an existing method's ability to classify different types of contributing factors and causation patterns, based on video recordings of critical situations in a naturalistic driving study (Paper III).

4. Examine the feasibility of using naturalistic driving data from whole trips for studying drivers' distribution of attention and how/if they adapt their engagement in visual-manual secondary tasks to the driving context in normal (non-critical) driving (Papers IV and V).

6. Summary of papers

This chapter presents an overview of this thesis, followed by a brief summary of the individual papers. For more detailed information, see the appended papers. The left side of Figure 2 shows the real world data sources used, the analysis performed, and the different types of factors investigated, indicated by the encircled numbers. The individual papers are related to the three main questions about crash contributing factors formulated in the overall aim. These questions are then related to applications of real world data in car safety development, shown in the gray field on the right side of the figure.

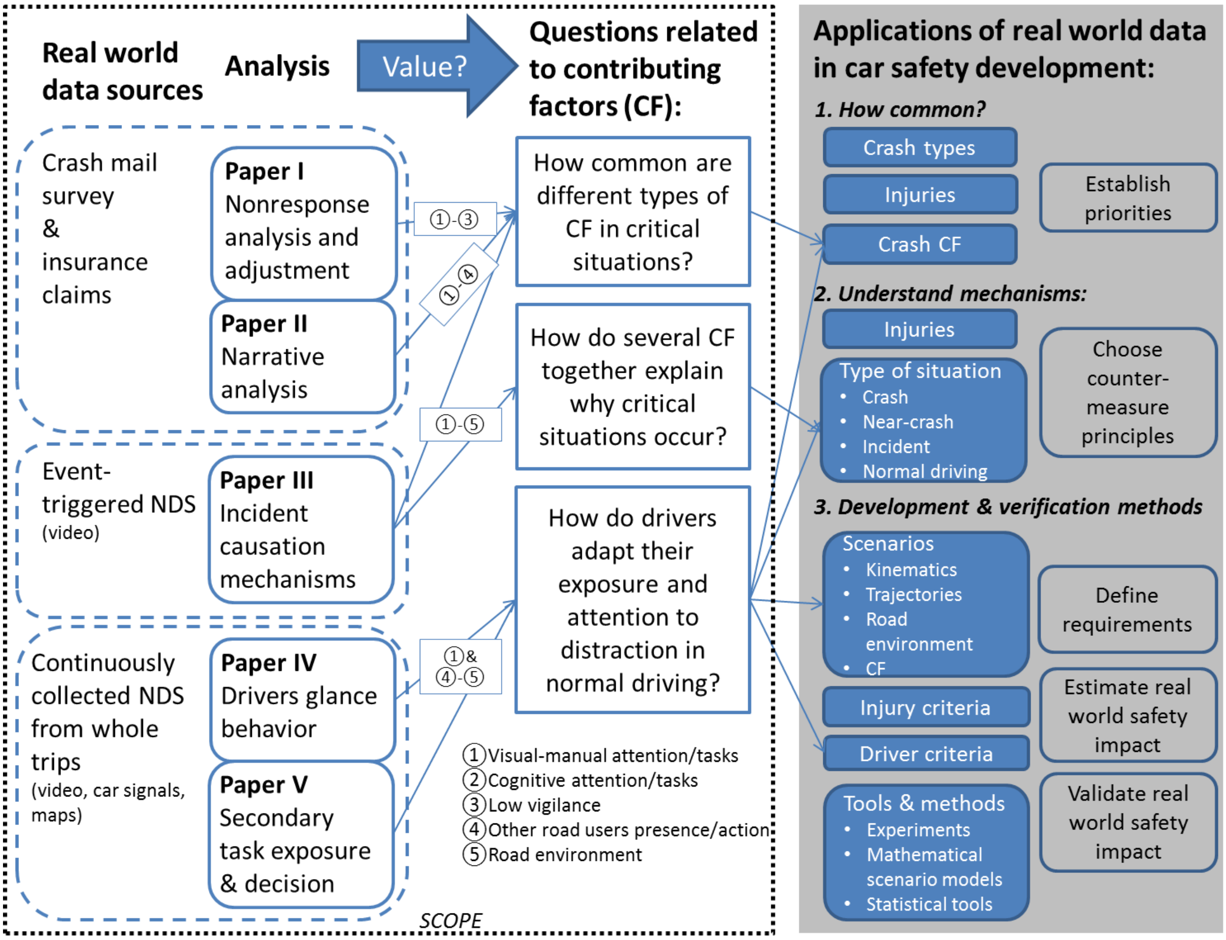

Figure 2: Overview of the individual papers illustrating how they relate to the main questions about contributing factors formulated in the overall aim, and how these questions relate to car safety development.

The investigated factors are related to visual-manual attention (requiring eyes and hands, for instance when dialing a phone number), cognitive attention (e.g., thoughts, problem solving), low vigilance (e.g., drowsiness, health issues, intoxication), other road users' presence/actions (e.g., lead vehicle present and/or braking) and the road environment (e.g., road curvature, permanent visual obstructions). Papers I and II include all types of critical situations, Paper III specifically studies car-pedestrian incidents, and Papers IV and V investigate drivers' engagement in visual-manual phone tasks in normal non-safety-critical driving in all type of driving contexts.

Summary of Paper I: *Nonresponse analysis and adjustment in a mail survey on car accidents.*

Introduction: The mail survey method is popular since many persons can be reached and a wide range of questions can be posed. Low response rates have, however, raised a concern about whether crash mail survey can be trusted as a source for making strategic decisions in car safety development.

Objective: The objective of this study was to analyze, and compensate for, nonresponse bias in a crash mail survey when estimating the prevalence of crash contributing factors related to driver behavior. To accomplish this, it was necessary to identify the most influential weighting variables.

Method: Auxiliary variables available for all mail survey recipients were retrieved from an insurance company database. Response propensity as a function of several independent variables (e.g., driver demographics, crash type) was modeled using logistic regression analysis. Survey weights were calculated as the inverse response probability. A split sample analysis was also performed to test how well the model would generalize to a different sample within the same population. Weighted and unweighted mail survey estimates were compared for driver distraction and low vigilance. The correlation between the survey estimates and the auxiliary variables was also investigated to identify the most important weighting variables.

Results: Driver age, driver gender, crash type, vehicle age, ownership (private/company), and size of town where the registered owner resides all influenced response propensity. Nonresponse weighting had a moderate influence on survey estimates on driver distraction and low vigilance. Driver age and crash type were the most influential weighting variables, since they were related to both response propensity and the survey variables. Driver gender and town size also had some influence, but not for all survey variables investigated.

Discussion: The findings on response propensity are in line with existing research. However, driver age had a surprisingly large effect, and the results for crash type were a new finding. Weighting had a moderate effect on the survey estimates of driver distraction and drowsiness/fatigue, which is quite encouraging for the future use of crash mail surveys with low response rates. It is important to analyze, and if necessary compensate for, nonresponse in all survey research even when response rates are fairly high, in order to improve the confidence in survey estimates. More detailed and complete auxiliary data can further improve this type of analysis in future.

Summary of Paper II: *What can the drivers' own description from combined sources provide in an analysis of driver distraction and low vigilance in accident situations?*

Introduction: Traditional crash databases usually contain a large number of cases, but limited information about the pre-crash phase. To date, it is unknown whether there are any reasonably reliable and affordable methods to capture driver state and behaviors during the pre-crash phase.

Objective: The objective of this study was to evaluate the additional value of analyzing narratives in a crash mail survey and insurance claims, compared to using mail survey variables alone, when investigating different crash contributing factors related to driver behavior.

Method: The prevalence of three contributing factors (low vigilance, secondary task distraction, and driving-related inattention) was estimated, based on mail survey variables for 977 crashes. A subset of 158 cases was randomized from the larger dataset. Narratives in the mail survey and insurance claims provided by the driver and other road users were analyzed. Each case was assessed for the presence of each contributing factor, the extent of agreement between different data sources and road users, and the additional information provided by the narratives in explaining why the crash occurred.

Results: Using the combined variable and word data, the case analysis identified the following as probable or confirmed contributing factors: low vigilance in 8% of the crashes, secondary task distraction in 11%, and driving-related inattention in 6%. There was good agreement between sources when several documents were available. The narratives frequently provided valuable additional information about the contributing factors. A clear relationship was found between survey variables and the case study results for low vigilance and secondary task distraction, while driving-related inattention was more difficult to capture.

Discussion: With the case study approach, the estimated prevalence of contributing factors was similar to or higher than that of traditional crash investigations. On the other hand, the results show considerably lower prevalence of the contributing factors compared to existing NDS studies. The prevalence of some contributing factors in the existing study may be underestimated, due to the role of biases such as recall and social desirability in self-reported data. Importantly, the narratives provide information about some aspects of driver behavior (e.g., loss of sleep, emotional state) that is not obtainable from naturalistic observations. The findings suggest that the case study approach may be useful for establishing safety priorities and understanding crash causation mechanisms, especially when combined with other types of data such as NDS.

Summary of Paper III: *Driver behavior in car-to-pedestrian incidents: An application of the Driver Reliability and Error Analysis Method (DREAM).*

Introduction: Understanding why and how safety critical situations such as crashes or incidents occur is essential for car safety development, but this information is difficult to obtain from traditional crash investigations. NDS offers new opportunities for studying driver behavior in critical situations. A basic premise of analyzing less severe events, such as incidents, is that the results will partially generalize to more severe events, such as crashes.

Objective: One objective was to evaluate the potential of using video recordings from an NDS to understand why critical situations occurred, by classifying the contributing factors and causation patterns observed. Another objective was to evaluate whether the causation patterns can inform the design of ADAS.

Method: A method of classifying contributing factors and causation patterns, called DREAM, was modified to suit the analysis of video recordings of incidents from an NDS. The method was applied to 90 car-to-pedestrian incidents recorded in Japan, all occurring at or near an intersection. The incidents were divided into three groups, based on differing causation patterns (i.e., drivers going straight at an intersection, turning at an intersection, or going straight away from an intersection).

Results: Contributing factors relating to drivers' visual behavior, the driving task, the road environment, and the behavior of other road users were directly observable from video, and commonly captured. Cognitive demand and expectancy of other road users' behavior were also captured, but these rely on the analyst's interpretation of driving demand. Driver states and strategic circumstances were, however, not identified in the present study.

Discussion: The results show that DREAM can successfully be applied to video recordings of critical situations in NDS. The NDS data provided detailed information on drivers' visual attention, the road environment, and the presence and actions of other road users. The present study had a higher prevalence of crash contributing factors related to driver distraction/inattention, and temporary visual obstructions (e.g., other vehicles) compared to a previous study based on in-depth investigations of car-to-pedestrian crashes. It is possible that there are important differences between incidents and crashes, but the data collection approach is likely to explain part of the differences between the two studies. The causation patterns resulting from this study are useful for informing the design of ADAS on a conceptual level.

Summary of Paper IV: *Driving context and visual-manual phone tasks influence glance behavior in naturalistic driving.*

Introduction: Visual-manual secondary tasks (e.g., text messaging, navigation entry) are associated with an increased risk of crashes/near-crashes. Tasks that require many glances and a high proportion of long glances away from the road are of special concern for safety. However, the effect of driving context (e.g., turning, lead vehicles) on glance behavior has not been thoroughly investigated in real world driving. The extent to which drivers adapt their glance behavior to changes in the road environment during secondary tasks is likely to influence their ability to compensate for and respond to changes in the road environment.

Objectives: One objective was to investigate the effect of driving context and visual-manual tasks on drivers' eye glance behavior. Another objective was to evaluate NDS data as a source for analyzing drivers' glance behavior in different contexts and during secondary task engagement.

Method: This study used continuously recorded NDS data from whole trips, including video recordings (e.g., driver, traffic environment), and car measurements (e.g., speed, yaw rate). Video recordings of 366 trips were reviewed to identify instances of drivers' dialing, texting or reading on their phones. Detailed coding was performed for the 109 identified phone tasks, including baseline driving prior to each task. Drivers' on/off road glances and the driving context (i.e., turning, presence of lead and oncoming vehicles) were coded. Several eye glance metrics were analyzed to investigate how glance behavior varied with driving context and secondary task engagement.

Results: The drivers' glance behavior was sensitive to turning maneuvers and the presence of other vehicles (e.g., oncoming, lead vehicle), both at baseline and during phone tasks. Driving speed did not influence glance behavior in baseline driving, while it had some influence during phone tasks. The glance metrics capturing long glances are the most effective for distinguishing between tasks, and between driving contexts during tasks. The percentage of time looking at the road, in contrast, is more effective for distinguishing between driving contexts in baseline driving.

Discussion: Continuously collected NDS data from whole trips are an excellent source for studying drivers' eye glance behavior in normal driving. Several glance metrics and context variables are necessary to reliably assess drivers' visual distraction. Driving context combined with glance behavior could improve distraction detection algorithms, influence the sensitivity of driver support functions (e.g., forward collision warning), and guide the selection of driving scenarios for evaluating in-vehicle user interfaces and driver support functions.

Summary of Paper V: *Driving context influences drivers' decision to engage in a visual-manual phone task: a naturalistic driving study.*

Introduction: In addition to the crash risk while engaged in a secondary task, the overall safety impact of driver distraction is influenced by how often, and under which circumstances, the drivers choose to engage. Driving simulator studies show that drivers adapt to the demand of secondary tasks by increasing their safety margin (e.g., reducing speed, increasing distance to a lead vehicle). Questionnaire surveys show that drivers' age, personality, task motivation, and, to some extent, driving demand (e.g., maneuvers, speed) influence their decisions to engage in secondary tasks.

Objective: The objective of this study was to explore the value of using NDS data from whole trips to analyze drivers' decisions to engage in secondary tasks, with respect to task timing and overall propensity to engage.

Method: Video recordings from 1432 whole trips from an NDS were reviewed. Trip purpose, passenger presence, light conditions, and instances of visual-manual phone tasks (i.e., dialing, texting, reading) were coded. Driving context (i.e., turning, presence of other vehicles) was coded for 374 identified phone tasks and for baseline driving prior to each task. The effect of driving context on drivers' overall propensity to engage in a phone task was investigated by comparing all driving to instances when the driver initiated a phone task. Task timing was investigated during a time interval starting 15 seconds prior to each task.

Results: Task timing and the overall propensity to engage in a phone task were influenced by speed and turning maneuvers, but not by lead vehicle presence. In car-following, drivers tended to engage in phone tasks when the lead vehicle increased speed while the driver maintained speed, resulting in increasing time headway. In contrast to driving simulator studies, there was no evidence of drivers reducing speed as a consequence of phone task engagement.

Discussion: NDS data from whole trips capture genuine driver behavior in normal day-to-day driving that may differ from driver behavior in an experimental setting. NDS data enable an analysis of the influence of driving context on the overall propensity to engage in secondary tasks, as well as an analysis of task timing. The results for task timing suggest that drivers' decisions to engage in secondary tasks are influenced at the tactical level. Research on drivers' decision styles, adaptive behaviors, and individual differences could greatly improve our understanding of exposure to driver distraction. Future studies should include NDS, surveys, and focus groups, with a sample of participants resembling the driver population, to fully cover important aspects of drivers' decision-making processes.

7. Discussion

Using real world data is necessary to reveal the safety problems that exist in real life. Real world data are used in car safety development to estimate the prevalence of crash types, injuries, and crash contributing factors, as well as to understand the mechanisms explaining why crashes and injuries occur. This information is an essential part of car safety development, facilitating problem prioritization and the selection of countermeasures that effectively address injury and crash causation mechanisms. The present thesis focuses on investigating the potential of analyzing data from mail surveys, insurance records, and naturalistic driving studies, in order to determine how common different contributing factors are, how they together can explain why critical situations occur, and to investigate drivers' exposures and decisions to engage in secondary tasks. Specifically, this chapter discusses the value of methods for: (1) compensating for nonresponse in a mail survey; (2) analyzing narratives provided by road users involved in a crash, using mail survey and insurance claim documents; (3) analyzing causation based on video recordings of critical situations from a naturalistic driving study; and (4) analyzing drivers' adaptive engagement and management of visual-manual tasks in normal driving, using naturalistic driving data from whole trips. Finally, sections 7.4 and 7.5 discuss the implications of using different data collection and analysis methods in car safety development and for other parts of the road transportation system.

7.1 Improving the estimated prevalence of crash contributing factors in a crash mail survey by using insurance claims

The mail survey method is a cost-efficient method for gathering statistical crash data (Dillman, 1991). In order to use mail surveys to establish priorities, it is essential to consider the different sources of survey error.

7.1.1 Nonresponse analysis and adjustment (Objective 1)

The study in Paper I investigated the influence of nonresponse in a crash mail survey. The results show that crash type, driver age, driver gender, type of ownership, vehicle age, and the population of the place of residence all influenced how likely the crash-involved drivers were to respond to the survey. Most of these findings are in line with existing research on mail surveys from other research areas (Groves, 2006). The influence of driver age on response propensity was surprisingly large compared to previous studies, and the influence of crash type was a new finding. While the weighting variables provided a very general classification of crash types, the survey itself contained a more detailed classification. Consequently, the weighted mail survey data in Paper I can be used to gather general information for a large number of crashes, and to establish priorities by pinpointing the most frequent crash types according to the classification in the survey.

The results identified driver age and crash type as the most influential weighting variables since they were both related to response probability and the investigated crash contributing factors (i.e., low vigilance, driver distraction). Nonresponse analysis and adjustment (if necessary) is a prerequisite for achieving representative data from questionnaires, even if response rates are fairly high (Groves, 2006). Ignoring nonresponse could lead to underestimating contributing factors associated with young drivers and specific crash types (e.g., run-off-road), where the response rate is low. However, the results from Paper I revealed that survey estimates for driver distraction and low vigilance (including drowsiness, fatigue and health issues) were only moderately affected by nonresponse weighting. The findings from Paper I suggest that compensating for nonresponse bias in mail surveys can improve confidence in the results, making them more useful for strategic decisions in product development. Even though these results are promising, it is important to keep in mind that nonresponse analysis and adjustment can only be accomplished for those variables that are available for all mail recipients. Other factors, such as personality, may also be important for response propensity, although they are not typically available as auxiliary data. Furthermore, drivers are probably less likely to respond to a mail survey if a punishable offense (e.g., speeding, alcohol, severe drowsiness) was a contributing factor. This reluctance may partly explain the low response rate for single-vehicle collisions since the drivers themselves were more likely to be entirely responsible. Animal collisions, on the other hand, had a high response rate. In Paper II, animal collisions were typically described by the drivers as highly unpredictable events, which may increase their willingness to respond to the survey. Thus, the estimates of crash contributing factors from a mail survey can be improved by performing nonresponse analysis and adjustment. This will increase the confidence in the results when using the data to make strategic decisions about what crash types and contributing factors should be addressed for car safety development. However, the results in Paper I are only adjusted for the influence of nonresponse. Measurement error related to memory and social desirability are difficult to control for, and some contributing factors may still be underestimated. It is therefore advisable to use additional data sources such as NDS to estimate the prevalence of different crash contributing factors.

7.1.2 The value of analyzing narratives (Objective 2)

The results from Paper II showed that the narratives in crash mail survey and insurance claim documents provide valuable additional information about crash contributing factors not available from the mail survey variables alone. The narrative analysis can improve the crash investigation by providing (1) insight into the drivers' interpretations of the survey questions, (2) more specific explanations about why the crash occurred, and (3) information on crash contributing factors that were not considered by the survey questions.

The results in Paper II show that the estimated prevalence of different crash contributing factors may be improved by analyzing narratives. The estimated prevalence of low vigilance and driver distraction, which were covered by the survey questions (e.g., mobile phone use, radio/CD, own thoughts), remained unchanged. However, external distraction (e.g., looking at roadside scenery) was not covered by the survey questions, and captured instead in the narratives. In contrast, driving-related inattention (e.g., looking for a road user other than the one that the driver collided with) was difficult to capture from the narratives. One explanation is that it is difficult to self-report visual attention, since visual search is a largely automated behavior that is difficult to recall. Another explanation is that the survey question about driving-related inattention was open to different interpretations. For instance, when drivers indicated that another vehicle or pedestrian required their attention prior to a crash, they could have been referring to the road user they were about to collide with, or to another road user who may not even have been relevant to the traffic situation. These results show that narrative analysis can improve the estimated prevalence of crash contributing factors, but they also point to areas where the questionnaire design can be improved. For instance, adding a survey question asking about external distraction, and rephrasing the question about driving-related inattention could possibly improve the estimates for these factors.

The data in Paper II do not, however, provide information about the influence of social desirability or the driver's recollection of the crash. Consequently, the prevalence of distraction and low vigilance may be underestimated due to social desirability and drivers' ability to recall what happened just before the crash. Driving under the influence of alcohol is one example of a crash contributing factor that may be especially vulnerable to social desirability bias (Lajunen & Summala, 2003). Police reports may be a better source for contributing factors related to alcohol impairment, since alcohol levels are commonly measured by the police at the scene of the crash. Descriptions from the driver and other involved road users and witnesses, when available, can provide a basic check on survey validity. In many of the cases, however, information was available only from the responding driver, particularly in single vehicle collisions.

Hence, narratives provided additional value when analyzing mail surveys and insurance claims. Information on the validity of survey estimates of crash contributing factors is, however, somewhat sparse. This approach may therefore be best suited to providing a better understanding of those contributing factors that can be captured with self-report methods, complementing in-depth on-scene crash investigations and large-scale NDS studies.

7.2 The value of video recordings of critical situations when analyzing contributing factors and causation patterns (Obective 3)

The results from Paper III demonstrate that analysis of video recordings of critical situations in NDS data provides detailed information about contributing factors related to the road environment, other road users' behavior, and the visual and operational behavior of the driver. Assessing cognitive demand, on the other hand, relies on the analysts' interpretation, based on other cues such as complexity of the traffic situation and/or tasks performed by the driver. In addition, some factors related to expectations about the other road users' behavior required knowledge about the local traffic rules and culture, and what can be considered normal behavior. There were several contributing factors available in DREAM related to driver traits (e.g., sensation-seeking), driver states (e.g., drowsiness) and strategic circumstances (e.g., time pressure) that were not captured in the short video sequences analyzed in the present study. The fact that driver drowsiness was not identified in the present study could have different explanations. There were only 90 incidents analyzed, and it is possible that drowsiness was not actually present, since most incidents occurred at intersections during daytime. Another explanation could be that it is difficult to detect drowsiness from video recordings of the driver. Indeed, in an on-road experiment, Fors et al. (2013) found that there was poor agreement between observer ratings of driver drowsiness from video recordings and drivers' self-rated level of drowsiness. On the other hand, the 100-car study used observer ratings of drowsiness, and found moderate to severe drowsiness in 4% of the video clips representing normal driving (i.e., baseline epochs). Drowsiness was associated with a fourfold increase in crash/near-crash risk (Klauer et al., 2006). Consequently, it is possible to observe driver drowsiness from video recordings, but its prevalence may be underestimated, with the exception of severe drowsiness (e.g., drivers falling asleep at the wheel).

The results from Paper III highlight the advantages of observing driver behavior under naturalistic driving conditions. Aspects of driver behavior that are missed or only partly captured in self-reported data can be captured. In particular, past crashes, incidents, and driver behavior are prone to under-reporting in self-reports (Lajunen & Özkan, 2011).

Although medium- or small-scale NDSs generally contain few crashes, incidents can be studied as surrogates for crashes. Incident analysis can provide an understanding of why the drivers ended up in critical situations, and how they resolved them. The assumption that incidents will partly generalize to crashes is quite reasonable, but it is not exactly known how valid this assumption is. Future large-scale NDSs may, however, provide more data on actual crashes and near-crashes. It is likely that the present focus on incident investigations will be redirected towards comparing incidents to crashes, to consider why some situations result in crashes while others are resolved by the involved road users.

The analysis method used in Paper III is applicable to more severe events, such as crashes and near-crashes. Analyzing video recordings of crashes and near-crashes could reveal causation patterns which differ from the ones investigated in the present study. Those in the present study differed from the patterns in a similar analysis, which was based on in-depth investigations of car-pedestrian crashes (Habibovic & Davidsson, 2011). In particular, the results in Paper III had a higher prevalence of crash contributing factors related to driver distraction/inattention and temporary visual obstructions (e.g., other vehicles blocking the view). These differences may in part stem from differences between incidents and crashes, but the data collection approach may be an even more pertinent explanation. There is no physical evidence of drivers' attention allocation and temporary visual obstructions at the crash scene, so when an in-depth crash investigation team arrives this information needs to be obtained from interviews with the involved road users. The ability to use event-triggered NDS from incidents as well as crashes to scrutinize causation mechanisms is useful in car safety development, because it can guide the choice of ADAS that aim to support the driver in critical situations, as illustrated by the findings of this study. The 100-car study was the first to identify the frequency of different contributing factors in crashes, near-crashes and incidents (Dingus et al., 2006). Paper III, on the other hand, is the first study to demonstrate how contributing factors can form causation patterns, based on video recordings from NDS data.

7.3 The value of continuously recorded NDS data from whole trips for analyzing drivers' decisions to engage in a secondary task and their distribution of attention (Objective 4)

The results from Paper V reveal that when considering normal driving in NDS data from whole trips, several context variables, including passenger presence, influenced how likely a driver was to engage in a visual-manual phone task. The results show that drivers were less likely to engage when the driving demand was high (e.g., high speed, turning maneuvers) or when a passenger was present, and more likely when driving demand was low (e.g., while standing still). The influence of speed has been demonstrated in a previous NDS study (Funkhouser & Sayer, 2012). The results from Paper V imply that on-site observational studies investigating the use of mobile phones by observing drivers stopped at intersections (NHTSA, 2014) are likely to overestimate the exposure of visual-manual phone tasks. The results from the present study are also supported by previous studies using focus groups and surveys, which indicate that drivers to some extent avoid complex secondary tasks on winding roads as well as during turning and merging maneuvers (Lerner et al., 2008; Young & Lenné, 2010).

The results presented in Paper V for drivers' task timing clearly show that drivers' decisions to engage in visual-manual phone tasks were influenced at the tactical level. Drivers waited to initiate phone tasks until after executing driving tasks such as sharp turns, lane change maneuvers, and complete stops. Lead vehicle presence did not influence drivers' decisions to engage in a phone task, although the drivers did adapt the timing of phone tasks to situations where the lead vehicle was increasing speed, resulting in increasing time headway. This result is consistent with a naturalistic driving study by Fitch et al. (2013) that found increasing time headway when drivers were sending a text message, compared to matched baseline driving prior to the task. Driver exposure to visual-manual tasks does not seem to take place at random; drivers choose driving situations that permit a high secondary task demand. Consequently, drivers' exposure to secondary tasks in different driving contexts needs to be taken into account when selecting scenarios for evaluating ADAS and in-vehicle user interfaces. Context-dependent exposure to secondary tasks should also be considered when estimating crash risk and the overall safety impact of different tasks and behaviors.

The drivers did not reduce driving demand (e.g., reduce speed) at the operational level as a consequence of secondary task demand, a finding in contrast to existing driving simulator studies (Engström, Johansson, & Östlund, 2005; Kircher et al., 2004; Törnros & Bolling, 2005). The drivers did, on the other hand, adjust their glance behavior to the driving task demand, with shorter off-road glances when turning or in the presence of other vehicles (e.g., oncoming, lead vehicle), as shown in Paper IV. These results suggest that it is important to take driving context into account when evaluating drivers' glance behavior, whether they are engaged in a secondary task or not. Including both driving context and glance behavior could improve driver distraction detection algorithms, providing a more accurate assessment of visual distraction. This information could be further used to determine context- and attention-sensitive timing for driver information and warnings. Furthermore, these results illustrate that NDS data provide the opportunity to perform quite detailed analyses on driver behavior in normal driving conditions.

The subjects in Papers IV and V were mainly experienced drivers, and there was a lower proportion of young drivers than in Sweden's driving population. The results should therefore be interpreted as valid for experienced drivers rather than for Sweden's drivers as a whole. Young drivers are more likely to use electronic devices while driving, and they might be less influenced by driving context when deciding to engage in secondary tasks than more experienced drivers (Lee, 2007). The results from Papers IV and V imply that experienced drivers are good at deciding when to engage in secondary tasks and at adapting their distribution of attention based on the current and anticipated driving task demands. There were, however, certain situations that did not seem to influence drivers' decision to engage in visual-manual phone tasks, although the possibility of a critical situation is elevated (such as going straight at an intersection or the presence of a lead vehicle). As a result, drivers who engage in visual-manual tasks may be more vulnerable to unexpected events, such a lead vehicle braking or another vehicle without the right of way entering the intersection. ADAS that are sensitive to both driving context and drivers' visual distraction could detect when drivers fails to adapt to the current driving situation.

7.4 The value of analyzing different sources of real world data: Implications for car safety development (Overall aim)

Self-report and observation methods are two different approaches to collecting real world data that seek to reveal crash contributing factors in order to explain why crashes or incidents occur. The first asks the driver and other road users about the crash after it has occurred, while the second observes the situation as it unfolds. The results from the present thesis show that these two approaches differ in their ability to provide information on different types of crash contributing factors. Figure 3 provides an overview of the investigated factors, and indicates whether they were close to consistently captured (solid black arrows), probably underreported (solid gray arrows), or not identified (dashed gray arrow)by the respective method. The right side (gray) in the figure shows the applications of real world data in car safety development.

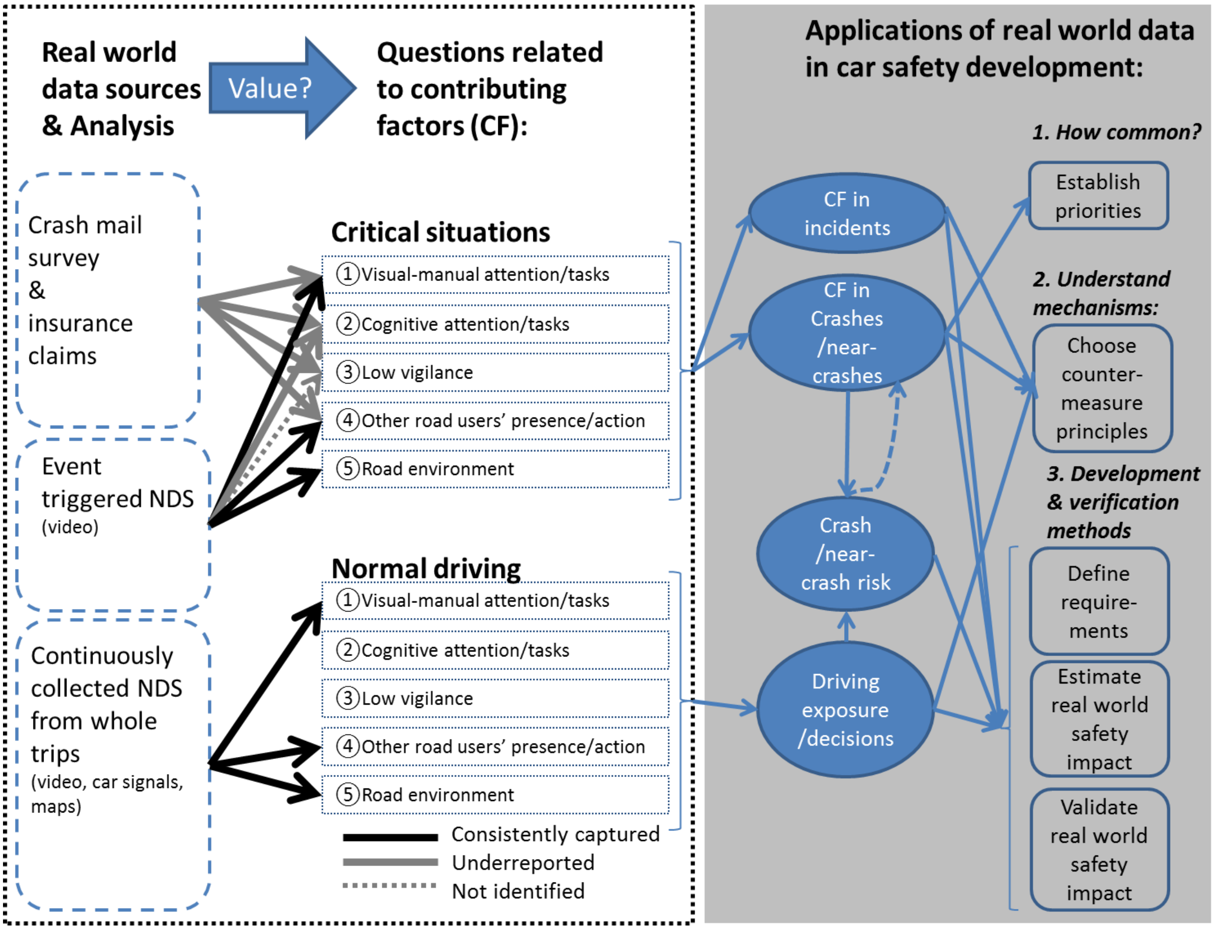

Figure 3: The contributing factors investigated in this thesis, using different sources of real world data (left) and the use of contributing factors in car safety development (right).

Depending on data source and analysis approach, different factors were consistently captured, underreported or not captured at all. This finding suggests that car safety development can benefit from combining different types of real world data sources to get a more complete and comprehensive picture of the contributing factors that exist, and how common they are. The choice of data sources and analysis approach will influence car safety development in several ways, as indicated by Figure 3. These implications are discussed in the following sections.

7.4.1 Establishing priorities

Strategic decisions about car safety development are influenced by the relative prevalence of different crash types, injuries, and crash contributing factors. Since different contributing factors are captured depending on the approach(es) taken, the selection of real world data sources and analysis methods will influence the decisions made.

In addition, the data sources need to provide a sufficiently large number of crashes representative of a population of drivers in a country, preferably for several countries representing different parts of the world. The results from the mail survey and insurance claims presented in Papers I and II provide representative data on different crash types for all new cars of a specific brand involved in crashes in Sweden, although several crash contributing factors are underreported. The NDSs investigated in Papers III, and IV-V were, on the other hand, able to consistently capture some of the investigated crash contributing factors. However, the data was restricted to experienced drivers in a specific region, and contained few crashes.

Event-triggered NDS is an extremely effective way to collect data from a large number of critical events in vehicles. In future, all production cars could be equipped with advanced event data recorders (EDR), which collect comparable data. Currently, large-scale event-triggered NDS is offered as an add-on system (Engström, Werneke, et al., 2013), mainly targeting professional truck drivers and teen drivers. While the 100-car study and other NDSs of similar size have increased the understanding of lead vehicle crashes and near-crashes, large scale NDS/EDRs can provide information on a wider range of rare types of critical situations with a high injury risk in case of a crash (e.g., oncoming vehicle, run-off-road crashes).

What if a really advanced EDR that included video recordings could be included in all cars worldwide – would that remove the need for mail surveys to collect crash data? Not entirely, because mail surveys and other self-report methods can provide information that is not available through observation alone. Questions that are addressed in the EDR recording or extremely difficult to answer due to errors of estimation or recall, could be omitted in the mail survey. The mail survey questionnaire would be much shorter, likely increasing the response rates. Nonresponse analysis would still be essential, however, since higher response rates would not guarantee that nonresponse bias does not exist because it occurs as a function of how correlated the response propensity is with what is measured in the survey. Combining mail survey data, video recordings, and other crash measurements would create a more complete picture of crash contributing factors and causation mechanisms. However, personal privacy concerns needs to be considered when it comes to using large-scale video recordings from actual crashes in production vehicles.

Another important issue to consider is the ability to distinguish between contributing factors and other circumstances that did not contribute to the crash. It is difficult to know if an observed behavior is a contributing factor or not when only critical situations are analyzed. For instance, the fact that someone was talking on the phone at the time of a crash does not necessarily mean this behavior was a contributing factor to the crash. In fact, recent analysis of NDS data has shown that talking on the phone is not associated with an increased crash risk (Olson et al., 2009; Klauer et al. 2006). Consequently, this behavior would not usually be considered a contributing factor, but it could still be in some specific situations (e.g., an emotional conversation, driving through a complex intersection). Estimating crash risk is therefore important for helping distinguish between contributing factors and other circumstances. More scenario-specific risk estimates could improve this knowledge in the future. Driving exposure and crash data from the same types of data sources are necessary to reliably estimate the crash risk of different driver activities and behavior metrics, since the data sources differ in the selection of drivers and in their ability to capture different crash contributing factors.

7.4.2 Selecting countermeasure principles

Crashes are rare, unpredictable events that cannot be explained by a single contributing factor (Huang, 2007). Selecting countermeasures that address individual contributing factors may therefore have only limited impact in real life safety. Instead, it is necessary to understand how several different contributing factors together explain why crashes and other critical situations occur, in order to select countermeasures that effectively address these mechanisms. The method used in Paper III for analyzing incident mechanisms, based on video recordings from an NDS, could be applied to more severe events such as crashes and near-crashes from large-scale NDS/EDR data. In-depth crash investigations with high-quality data in the pre-crash phase can, to some extent, provide information on contributing factors that may be present during normal driving before the crash. Event-triggered NDSs are, however, limited to the time just before and after the trigger criteria for data collection (e.g. a certain braking level), mainly restricting the available information to the critical situation. While crash investigations can provide an understanding of how to support drivers in critical situations, they usually contain limited information on the potential to support the driver in normal driving.

Normal driving and incidents can provide useful information about the safety margins which individual drivers prefer to maintain while driving (Summala, 2007). Studying both normal driving and incidents makes it possible to estimate the driving conditions in which the drivers deviate from their comfort zone and feel discomfort. The comfort zone boundary can be used to define the thresholds for several driver support functions. For instance, a driver may appreciate an early warning when a lead vehicle is braking and he or she is engaged in a visually demanding secondary task. The threshold could be set by the driver's comfort zone boundary, to provide a warning well before the situation is considered safety-critical by system designers.

The analysis performed also depends on how we interpret the data, which is in turn guided by the current understanding of driver behavior and why crashes occur. Analysis frameworks such as DREAM, which reflect what we know today, need some flexibility to be updatable with new research findings.

7.4.3 Other implications of using real world data for car safety development

The results presented in this thesis may also have other implications for car safety development not discussed in the previous sections. For instance, the methods for analyzing drivers' visual behavior, secondary task engagement, and driving context in normal driving conditions in NDS could facilitate car safety development in several ways: (1) by helping refine driver distraction detection algorithms, (2) by setting targets for the development of sensors to monitor driver state and the traffic environment, and (3) by providing input to computational models describing normal driver behavior. Computational models can be used for more than increasing our understanding of driver behavior: they can also be used for evaluating systems which aim to support the driver in normal driving and in critical situations. Normal driving behavior could be combined with unexpected events in order to simulate critical situations, since the combination of distraction and a sudden event has been commonly identified in critical situations in previous NDSs (Dingus et al., 2006). Thus, much can be learned from analyzing driving behavior in non-critical driving. The results can improve the product development process in formulating requirements and provide a means of evaluating different safety systems which support the driver in normal driving as well as in critical situations.

Estimating the overall safety impact of different design concepts includes estimating not only the number of crashes, but also the number of injuries. The latter requires a nested function of *driving exposure-crash risk-number of crashes,* and *number of crashes-injury risk-injury outcome,* corresponding to well-established analysis methods within car safety development (Korner, 1985). These estimates form the building blocks for establishing priorities for car safety development that encompass both crash and injury prevention.

Once new cars are on the road, there is a need to verify that the cars and drivers perform as intended in real life situations. Since the driver support functions develop rapidly, it is essential to get information on their real-life performance as soon as possible. However, it usually takes years of crash data to verify the performance of introduced safety systems (Erke, 2008; Evans, 1999; Jakobsson et al., 2010). There are two ways to tackle this limitation: (1) Select a larger region for crash data collection, or (2) include near-crashes and low-severity crashes. Collecting data from crashes all over the world with large-scale EDRs would be one way to do this. The second alternative has been implemented in the EuroFOT project, which used instrumented vehicles in a field operational test (FOT) (Malta et al., 2012). Other aspects such as take rate for non-standard systems, user acceptance and usage of the systems (e.g., if they have them switched on) also affect real world safety performance. As a result, both FOTs and questionnaires can be useful to find out if and how the drivers use a certain support system, and what they think about it.

Results from the analysis of real world data vary greatly in quality and validity. No data source or analysis method will provide exact numbers on how common different contributing factors are. There are a number of basic requirements for real world data analysis: (1) Know what safety problems exist, (2) Know their order of importance, (3) Trust the results enough to use them, and (4) Understand the mechanisms behind crash occurrence and different driver behaviors. Real world data analysis that meets these requirements can improve decision-making in product development projects by pinpointing the most urgent safety problems to address. Additionally, safety countermeasures can be developed that effectively address crash causation mechanisms.

7.5 General implications for the development of the road transportation system

This thesis mainly considers different methods for collecting and analyzing real world data for car safety development. It is, however, important to consider all components of the road transportation system when working towards national and global goals to reduce the number of people who are seriously injured or killed in traffic (WHO, 2013). Cooperation between road authorities, legislators, driver training programs, and vehicle manufacturers is one important key in reaching the ambitious goals and visions formulated by the different stakeholders (Eugensson et al., 2011; WHO, 2013). The results from the present thesis could also be of interest beyond vehicle development. For instance, the positive adaptation of secondary task engagement and distribution of attention used by experienced drivers, reported in Papers IV and V, could inspire training programs for novice drivers.

National safety development relies mostly on crash databases of police reported crashes in a specific country. However, vehicle manufacturers have the opportunity to collect data from vehicles all over the world, which can provide not only large datasets, but also an understanding of regional differences. Several different sources of real world data, including large scale EDR/NDSs, surveys, insurance claims, and focus groups, are needed to provide valuable knowledge to promote safety development of vehicles, infrastructure, legislation, and education towards Vision Zero.

8. Conclusions

The main conclusion from the present work is that no single source of real world data is sufficient on its own to identify crash contributing factors (e.g., drowsiness, distraction) and provide insights into crash causation mechanisms. Using different sources (i.e., naturalistic observation, self-reports) provides a more comprehensive picture of crash contributing factors: how common they are, how they interact to explain why crashes occur, and how driving context influences the exposure to driver distraction.

Specifically, it was found that crash mail surveys combined with insurance records can provide reliable estimates of different crash types. Although the prevalence of several crash contributing factors are likely underestimated, complementing the survey data with insurance data helps compensate for nonresponse bias related to crash type, liability, and driver demographics. Analyzing narratives in the mail survey and insurance claims provided insights into how the drivers interpret the questions, and in some cases captured detailed descriptions of contributing factors beyond the scope of the survey questions. It should be noted that contributing factors that the drivers are not aware of, cannot remember, or are unwilling to report will influence both nonresponse rates and the information provided.

An established method for classifying crash contributing factors and causation patterns from crash investigations was updated to analyze video recordings of critical situations in an NDS. The updated method was used to study car-pedestrian incidents. They contained detailed information about contributing factors that were directly observable from video, such as secondary task engagement, visual obstructions, and the drivers' visual behavior. On the other hand, identifying other contributing factors, such as cognitive demand and expectations about other road users' behavior, is more challenging since it relies on the analyst's interpretation. Furthermore, driver states (e.g., moderate drowsiness, internal thoughts) are difficult or impossible to assess with short video recorded sequences.

Additionally, continuously collected NDS data from whole trips were found to be an excellent source for studying normal driving behavior and engagement in visual-manual tasks, providing valuable insights into how drivers adapt their exposure, and how they manage their level of visual distraction. Analyzing NDS data from whole trips proved useful for studying how driving context (i.e., the presence of oncoming or lead vehicles, turning maneuvers, speed) influenced drivers' eye glance behavior, task timing and overall propensity to engage in a visual-manual phone task. Studying normal driver behavior can improve our understanding of exposure to different behaviors in driving, which is important when estimating crash risk and overall safety impact.

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