Bowtie Analysis without Expert Acquisition for Safety Effect Assessments of Cooperative Intelligent Transport Systems

Ute Christine Ehlers[1]; Eirin Olaussen Ryeng, Dr.Eng.[2]; Edward McCormack, Ph.D.[3]; Faisal Khan, D.Sc., M.ASCE[4]; and Sören Ehlers, D.Sc.[5]

Abstract: Estimating the safety effects of emerging or future technology based on expert acquisitions is challenging because the accumulated judgment is at risk to be biased and imprecise. Therefore, this semiquantitative study is proposing and demonstrating an upgraded bowtie analysis for safety effect assessments that can be performed without the need for expert acquisition. While bowtie analysis is commonly used in, for example, process engineering, it is novel in road traffic safety. Four crash case studies are completed using bowtie analysis, letting the input parameters sequentially vary over the entire range of possible expert opinions. The results suggest that only proactive safety measures estimated to decrease the probability of specific crash risk factors to at least "very improbable" can perceptibly decrease crash probability. Further, the success probability of a reactive measure must be at least "moderately probable" to reduce the probability of a serious or fatal crash by half or more. This upgraded bowtie approach allows the identification of (1) the sensitivity of the probability of a crash and its consequences to expert judgment used in the bowtie model and (2) the necessary effectiveness of a chosen safety measure allowing adequate changes in the probability of a crash and its consequences. **DOI: 10.1061/AJRUA6.0000986.** *© 2018 American Society of Civil Engineers.*

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Introduction

Cooperative intelligent transport systems (C-ITSs) are an emerging technology in automotive and transportation engineering, and expectations are high that their application will positively influence road traffic safety, among other transport-related issues. As with any other new or future technology, it is challenging to reliably estimate the effects C-ITSs might have. Facing this uncertainty and a lack of knowledge, research is often based on expert judgment. Unfortunately, this form of data, its elicitation as well as its interpretation, is prone to a large number of biases for various reasons (e.g., Eddy 1982; Meyer and Booker 1991; Tetlock 2005; Kirkebøen 2009; Kahneman 2011; Lees 2012; Morgan 2014). For instance, Kassin et al. (2013) provided a comprehensive overview of recent research indicating not uncommon confirmation bias among experts in various disciplines of forensic science. Confirmation bias is a psychological phenomenon "by which people tend to seek, perceive, interpret, and create new evidence in ways that verify their preexisting beliefs" (Kassin et al. 2013, p.44). In expert judgment in traffic safety, additional types of bias can be problematic, such as hindsight bias and publication bias (Shinar 2017). Hindsight bias, also called the "knew-it-all-along" effect, is the tendency to increase the perceived likelihood of an event or its outcome after the event has occurred. This bias embodies "beliefs about events' objective likelihoods, or subjective beliefs about one's own prediction abilities" (Roese and Vohs 2012, p.411) and thus can be problematic in the reconstruction and causation analysis of crashes (Dilich et al. 2006). Publication bias is the tendency not to publish negative results, which seems likely to also have an impact on the judgment of experts. Overviews of bias-reducing strategies and techniques that aim for high accuracy in expert judgment are provided in a number of publications (e.g., Meyer and Booker 1991; Kirkebøen 2009; Morgan 2014). For example, the use of explicit decision rules like the Bayes theorem and the training for it, or the incorporation of specific group decision processes, have been shown to reduce bias (e.g., Meyer and Booker 1991; Rowe and Wright 2001; Surowiecki 2004). Plus, in the absence of empirical data, the data accumulated in expert acquisitions seem to be the only data on which research can possibly be based. However, not even the best expert can exactly forecast the future performance of a specific novel system or the system's effects and their likelihood.

Another challenge comes in estimating the actual safety effects of C-ITSs in terms of their influence on crashes. Apart from implementing various C-ITSs with different levels of maturity in many different ways, long periods of exposure to real traffic are necessary to collect significant crash data. The majority of C-ITSs are still in the testing phase. Even applications whose deployment has already begun to a limited extent are far from providing enough real traffic and crash data to estimate safety effects in a statistically

[1]Ph.D. Candidate, Dept. of Civil and Environmental Engineering, NTNU Norwegian Univ. of Science and Technology, 7491 Trondheim, Norway (corresponding author). Email: ute.ehlers@ntnu.no

[2]Associate Professor, Dept. of Civil and Environmental Engineering, NTNU Norwegian Univ. of Science and Technology, 7491 Trondheim, Norway. Email: eirin.ryeng@ntnu.no

[3]Research Associate Professor and Director of the Master of Sustainable Transportation Program, Dept. of Civil and Environmental Engineering, Univ. of Washington, Seattle, WA 98195. Email: edm@uw.edu

[4]Professor and Canada Research Chair of Offshore Safety and Risk Engineering, Faculty of Engineering and Applied Science, Memorial Univ., St. John's, NL, Canada A1B 3X5. Email: fikhan@mun.ca

[5]Professor and Head of the Institute for Ship Structural Design and Analysis, Hamburg Univ. of Technology, 21073 Hamburg, Germany. Email: ehlers@tuhh.de

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reliable manner. Further, a substantial number of vehicles will have to be equipped with C-ITSs before the anticipated and actual safety effects will show. Due to this current lack of empirical data, research has been based on "by proxy" or surrogate methods to assess the effects of safety-related C-ITSs that are not yet implemented in real traffic or have been implemented for a relatively short time. By proxy or surrogate methods can be in-depth analyses of crash reports (Virtanen et al. 2006), ex ante estimate studies based on, say, crash data and statistics (Wilmink et al. 2008; Schirokoff et al. 2012), traffic simulation modeling, driving simulator and field test studies, or a combination of one or more of these (Harding et al. 2014). Ex ante estimate studies are based on in-depth crash investigations and analyze whether crashes or fatalities could have been prevented if a specific safety measure had been used (e.g., Vaa et al. 2014). These studies usually involve numerous assumptions regarding vehicle fleet penetration rates and infrastructure coverage, future trends, anticipated driver behavior, and functional and technological features of the studied system. Hardly any surrogate methods allow practical and fast safety effect estimation of new or future C-ITSs while allowing for the various factors associated with crashes and their consequences. Moreover, surrogate methods have one important disadvantage: crash risk is not measured directly. Instead, road safety is measured indirectly through performance indicators such as speed or driver behavior. Although their relation to or even correlation with crashes and their consequences is known to some extent, the true effects of ITSs, particularly on driver behavior, are still unknown, especially in the long term.

Ehlers et al. (2017) proposed bowtie analysis (BTA) as a probabilistic risk assessment method in road traffic safety to allow estimation of the safety effects of C-ITSs before their introduction or wide deployment. The authors consider bowtie analysis a valuable way to systematically and quantitatively assess the effects of safety measures, such as safety-related C-ITSs. It has been shown to be applicable when assessing changes in the probability of crashes and their consequences due to proactive or reactive safety measures. Proactive safety measures are here understood as measures to reduce the probability of crashes, whereas reactive safety measures are understood to reduce the probability of severe crashes. The proposed bowtie analysis is based on exemplary expert estimates created and applied solely for demonstration. These expert estimations were generated for the occurrence and success probability of specific events as fuzzy sets using linguistic terms, such as "highly improbable" and "moderately probable."

This study is an extension of Ehlers et al. (2017) and attempts to demonstrate an upgraded bowtie analysis by eliminating its dependence on expert acquisitions and thereby subjective expert opinions. Instead of involving experts, here bowtie analysis for four case studies allows the input parameters to vary sequentially over the entire range of possible expert opinions. The results for the case studies are then compared with a base case, whose input parameters ideally are based on existing knowledge and empirical evidence, such as crash statistics, in-depth analyses, and meta-analyses. This allows identification of (1) the sensitivity of the probability of a crash and its consequences to expert judgment and (2) the necessary safety effectiveness of a C-ITS allowing for adequate changes in the probability of a crash and its consequences. Thereby a method is created that aims to support public decision makers, such as road authorities, in identifying the minimum safety effectiveness required for emerging C-ITSs or other future safety measures without the need for expert acquisitions.

C-ITSs are created by placing information and communication technologies at the roadside and inside vehicles in order to collect, process, transfer, and deploy traffic- and safety-related data. Wireless short-range radio communication between the road infrastructure, vehicles, and personal electronic devices allows vehicle-to-vehicle communication (V2V) and vehicle-to-infrastructure communication (V2I). These information and communication links can be one way or two way. Cooperative vehicles (V2V) can "see" one another through wireless high-speed communication in real time and receive relevant data, such as position, speed, course, and vehicle type. Compared with noncooperative vehicles and transport systems, in cooperative vehicles information and warning timing are improved. System users receive information and warnings in real time, enhancing their situation awareness and providing them with additional reaction time. In addition, V2V-systems can augment sensor-based intelligent transport systems, thereby improving accuracy and support vehicle control (OECD 2003; Bayly et al. 2007; Harding et al. 2014).

The focus of this study is on safety-related C-ITSs that are expected to directly improve road traffic safety by reducing the probability of crashes and their consequences. Examples of (potential) applications are intelligent speed adaptation, emergency call systems, and various incident detection and warning systems (local danger warning, red light violation warning, curve speed warning, and the like). The "road traffic safety problem"—that is, the number of injuries and fatalities resulting from crashes—can be understood as a function of three variables: exposure, crash risk, and injury consequence, as shown in Eq. (1) (Nilsson 2004). In this equation, "accident" is synonymous with "crash."

$$\text{Number of injured} = \text{Exposure} \times \overbrace{\left(\frac{\text{Number of accidents}}{\text{Exposure}}\right)}^{\text{Risk}} \times \overbrace{\left(\frac{\text{Number of injured}}{\text{Number of accidents}}\right)}^{\text{Consequence}} \quad (1)$$

Exposure to the risk of traffic accidents is expressed, for example, in person or vehicle kilometers traveled. Accident rate is understood as the risk of a traffic accident per unit of exposure, often referred to as accident risk. The aforementioned concept of risk in road traffic safety should not be confused with the traditional definition: risk = probability × consequence, which is normally used in risk assessment and so is used in this paper.

The background to this study is covered by a short review of the theories behind bowtie analysis and fuzzy set theory. Crash scenarios, the base case, and additional assumptions taken from previous research are described as well. The framework used in this study is provided next, followed by descriptions of the four case studies. Finally, the results for all bowtie analyses and their implications are discussed and conclusions are presented.

Background

Bowtie Analysis and Fuzzy Set Theory

BTA is a recently proposed method in the field of road traffic safety (Ehlers et al. 2017), but it is commonly used in probabilistic risk assessment to qualitatively and quantitatively identify causes and consequences of a risk or hazardous event [Dianous and Fiévez 2006; Duijm 2009; IEC/ISO 31010 (IEC 2009); Jacinto and Silva 2010; Ferdous et al. 2012, 2013]. BTA combines two well-established risk assessment techniques, fault tree analysis and event tree analysis, but also includes safety barrier, or safety measure, elements. Its focus is on evaluating the effectiveness of both

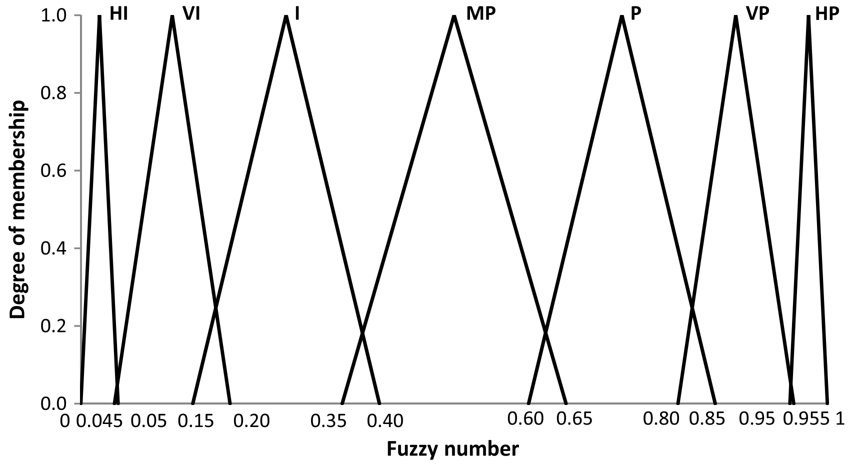

Fig. 1. Linguistic variables at fuzzy scale. (Reprinted from *Accident Analysis and Prevention*, Vol. 99, Part A, U. C. Ehlers, E. O. Ryeng, E. McCormack, F. Khan, and S. Ehlers, "Assessing the safety effects of cooperative intelligent transport systems: A bowtie analysis approach," pp. 125-141, © 2017, with permission from Elsevier.)

proactive and reactive safety measures to reduce or prevent a risk or to mitigate its consequences.

More specifically, a bowtie model and its diagram consist of the following events and safety measures, which are applied in this study:

- Causal (root) factors, here called basic events (BEs), initiating or contributing to system malfunction;
- Malfunctions, errors, and other faults and causes, here called intermediate events (IEs), causing the undesired critical event;
- Proactive countermeasures implemented, or planned, here called proactive safety measures (PSMs);
- The critical event (CE);
- Reactive countermeasures implemented, or planned, here called reactive safety measures (RSMs); and
- Consequences of the critical event, here called outcome events (OEs).

In quantitative BTA, the probability of basic and intermediate events acts as quantitative input together with the success probability of safety measures. The probability of the critical event as well as the outcome events represents the quantitative output and result of the analysis. In an ideal world, all input data would be known with high accuracy. In real life, however, absent or limited input data necessitate expert judgment, which tends to be subjective and possibly imprecise. Ferdous et al. (2012) presented a framework for handling both types of uncertainty in BTA using fuzzy set theory, which was adapted and applied in this study.

Fuzzy set theory has been proven efficient in handling subjective, imprecise information and noncrisp data such as linguistic expert judgment (e.g., Zadeh 1965; Bouchon-Meunier et al. 1999; Ayyub and Klir 2006; Markowski et al. 2009; Ferdous et al. 2012). For example, experts may use the term *set for probability* to estimate the probability of events and the success probability of safety measures, as in this study: highly improbable (HI), very improbable (VI), improbable (I), moderately probable (MP), probable (P), very probable (VP), or highly probable (HP). Such terms can then be converted to fuzzy numbers, such as triangular fuzzy numbers (TFNs), $x \in p$, to represent the membership functions (Bouchon-Meunier et al. 1999; Ayyub and Klir 2006). Using a numerical relationship, these describe the degree to which a number belongs to a set (Fig. 1). Each TFN P is then described as a vector, $\mathbf{p_L}$, $\mathbf{p_m}$, or $\mathbf{p_U}$, that is represented by the lower boundary, the most likely value (i.e., at the mode), and the upper boundary of P. Multiple and possibly inconsistent expert knowledge can be aggregated by the weighted average method (e.g., Ayyub and Klir 2006). After the input variables are assigned probabilities using TFNs, fuzzy arithmetic operations can be used to perform the bowtie analysis (Ferdous et al. 2012). These fuzzy arithmetic operations and equations are based on traditional equations from fault tree and event tree analysis, such as IEC 61025 (IEC 2006) and IEC 62502 (IEC 2010).

Crash Assumptions and Crash Scenarios

Although crashes are rare and random, in this study they are assumed to occur; that is, their probability is close to one. Thus, one crash and what is known as its causal chain are chosen because of the illustrative and demonstrative purpose of this study. This approach should not be confused with using actual probability or frequency of a specific crash type, which is based on crash data.

Ehlers et al. (2017) chose three illustrative crash scenarios, which were used in the case studies here. The following assumptions, valid for all of them, were made for a crash assumed to occur at a road section. The critical event was defined as a run-off-road collision of a single passenger car. More specifically, a single passenger car with one vehicle occupant is leaving the roadway at a section where a rock cut is located at the roadside. The speed limit for this section is 80 km/h. It is presumed that the vehicle occupant, the driver, wears a seat belt and that the vehicle collides with a guardrail meant to shield the rock cut.

The case studies were based on three safety measures, which can be distinguished as proactive or reactive in relation to the crash (Fig. 2). The first crash scenario was understood as the baseline, with two traditional safety measures. The other two scenarios were extensions of the baseline, with either a proactive or a reactive cooperative safety measure in addition to the traditional measures. Several basic and intermediate events, listed in Table 1, were chosen as parameters having the potential to initiate and cause the crash. That means that at least one basic event was assumed to initiate the crash, possibly in combination with at least one other basic event. The outcome events were defined using different injury severities classified according to the Maximum Abbreviated Injury Scale (MAIS 1–6). For example, MAIS 1 is a minor injury that requires short-term medical treatment such as stiches, whereas MAIS 6 is a fatal injury.

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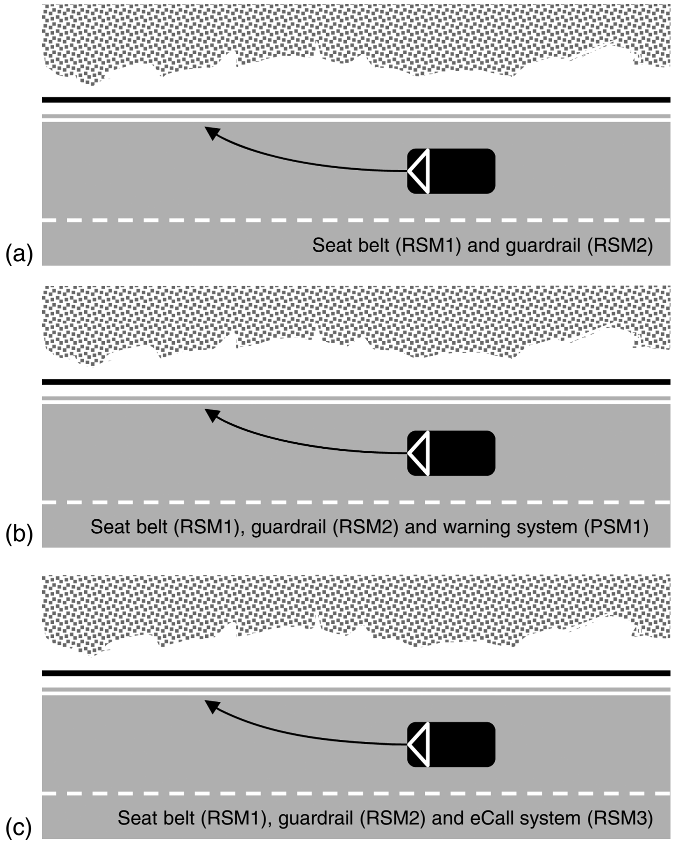

Fig. 2. (a) Scenario 1: baseline with two traditional reactive safety measures (RSM1 and RSM2); (b) Scenario 2: addition of one cooperative proactive safety measure (PSM1); and (c) Scenario 3: addition of one cooperative reactive safety measure (RSM3). (Adapted from Ehlers et al. 2017.)

Base Case and Its Bowtie Analysis

Ehlers et al. (2017) performed bowtie analyses for five case studies. The initial case study, and thus the initial bowtie analysis (BTA1), should be understood as the base case with which the results from this study are compared.

The base case was the baseline scenario with the two traditional and noncooperative safety measures, seat belt and guardrail. Fig. 3 shows the bowtie diagram developed for the base case and BTA1. The proactive safety measure (PSM) was added in BTA2 and was not part of BTA1. Short descriptions of BTA1's input and output events are provided in Table 2. The crash outcomes, and the resulting injury severities, were chosen based on the crash scenario and its underlying assumptions: that the driver sustains injuries due to the sudden and significant change in velocity given the speed limit of 80 km/h.

The probabilities of the input events for the quantitative bowtie analysis should be based on existing knowledge and empirical data. For example, the success probabilities for the reactive safety measures seat belt and guardrail were taken from Elvik et al. (2009) as fuzzy numbers: the probability of success for the driver's seat belt in a passenger car was (0.230, 0.280, 0.330); that for a guardrail was (0.365, 0.455, 0.530). However, it is important that the probabilities of the basic events were generated as example expert data because of the study's purpose to demonstrate bowtie analysis. In future research, it should be possible to use the actual approximate probability of the most representative basic events through crash statistics, thoroughly considering crash type, in-depth crash study results, and more. Ideally, the probabilities of the basic events would be chosen from an existing crash causation assessment study. Table 3 provides the generated occurrence probabilities and the chosen success probabilities of the input events at fuzzy scale.

Based on these input probabilities, the fuzzy based probabilities of the critical event (CE) and the different crash outcome events (OEs) were calculated using fuzzy arithmetic for bowtie analysis (Table 4). The calculated probability of the critical event was (0.839–0.998). Further, a crash with a critical or fatal injury (MAIS 5–6) was the most likely outcome calculated because a combined failure of the two traditional safety measures, seat belt and guardrail, whose success probabilities were judged to be relatively high, would have had serious consequences. Thus, the success of a safety measure means that it fulfills its tasks and performs as planned, under the assumption that it is provided and used as intended. The probability of the other crash outcomes was found to decrease with decreasing injury severity.

Table 1. Basic and intermediate events used in all case studies

Basic	Intermediate
BE1: Intoxicated driving	IE1: Driver error
BE2: Speeding; insufficient speed adaptation	
BE3: Inattention	
BE4: Fatigue, falling asleep	
BE5: Avoiding vehicle, bicycle, pedestrian, animal, object on driveway	
BE6: Impaired visibility (in-vehicle)	IE2: Vehicle malfunction
BE7: Steering defect	
BE8: Tire defect	
BE9: Brake defect	
BE10: Suspension defect	
BE11: Antilock braking system defect	
BE12: Electronic stability control defect	
BE13: Insecure load	
BE14: Dangerous road geometry design features	IE3: Infrastructure malfunction or environmental anomaly
BE15: Insufficient road signage or marking	
BE16: Poor road surface	
BE17: Reduced road surface friction	
BE18: Impaired visibility conditions (external)	

Source: Data from Ehlers et al. (2017).

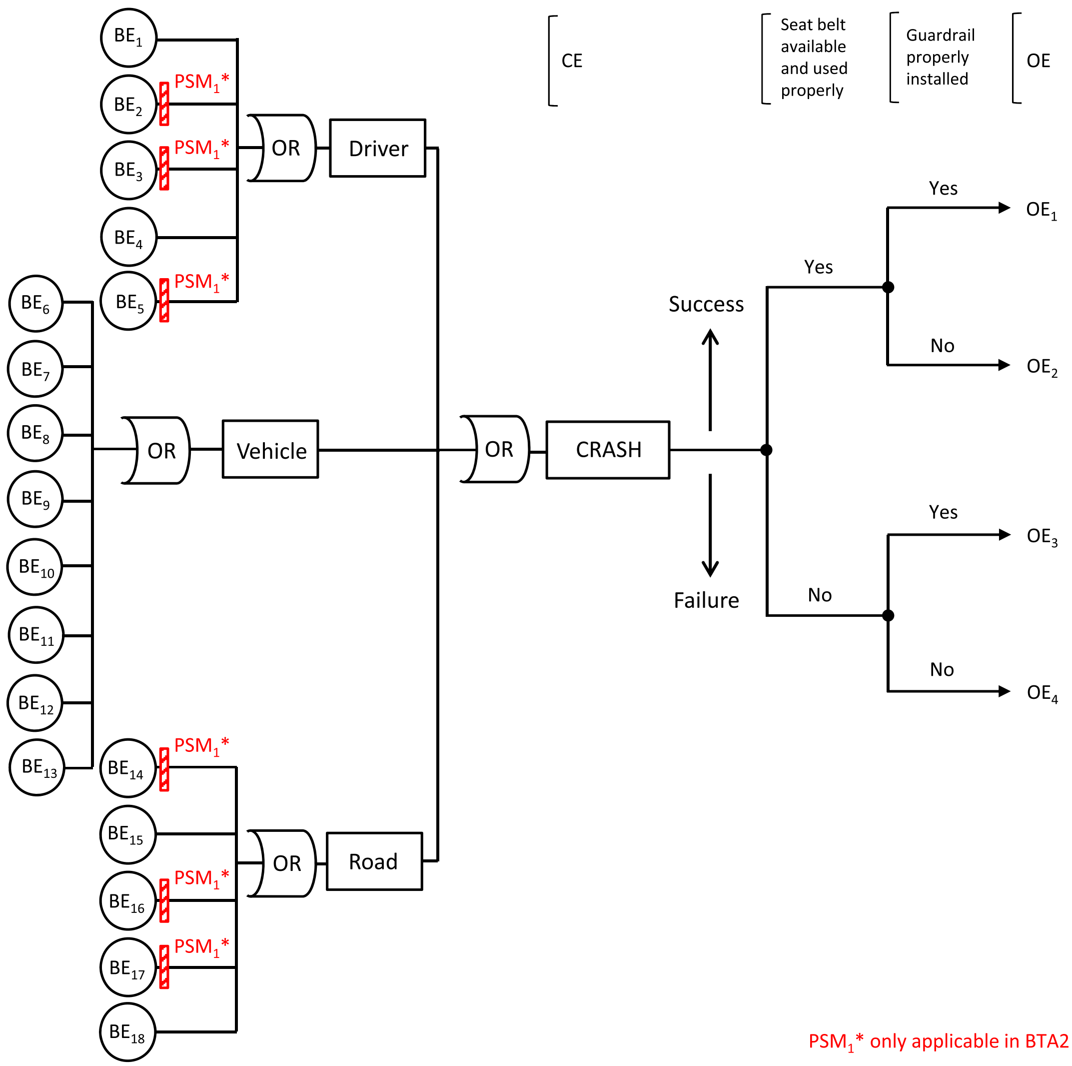

Fig. 3. Bowtie diagram for BTA1 and BTA2 with an additional cooperative proactive safety measure (PSM1). (Reprinted from *Accident Analysis and Prevention*, Vol. 99, Part A, U. C. Ehlers, E. O. Ryeng, E. McCormack, F. Khan, and S. Ehlers, "Assessing the safety effects of cooperative intelligent transport systems: A bowtie analysis approach," pp. 125-141, © 2017, with permission from Elsevier.)

Framework Used in This Study

In this study, a framework for bowtie analysis as a conceptual approach to evaluating the safety effects of C-ITSs (Fig. 4) was adapted from Ferdous et al. (2012) and Ehlers et al. (2017). It covered the full range of expert opinions on event probability. The quantitative bowtie analysis included a fuzzy approach with the following steps:

1. Generation of full-range expert opinion in the form of linguistic terms covering the entire range of event probability (highly improbable to highly probable) to define variations in probability of the input events due to a new safety measure.
2. Transformation of linguistic terms into triangular fuzzy numbers.
3. Aggregation of fuzzy numbers in case of opinions from multiple experts.
4. Determination of the probability of the critical event and outcome events through modified fuzzy arithmetic operations.

Probability assessments based on bowtie analysis using expert knowledge usually provide an approximate quantification of the likelihood of a critical event and its outcome events without considering the full spectrum of possible expert judgments. For example, if an expert makes a judgment in opposition to the judgment made by another expert, the judgment of all experts is aggregated and averaged using, for example, the weighted average method. Furthermore, although a fuzzy approach allows the handling of subjective and imprecise expert judgments to a certain extent, it cannot cover all parameter uncertainties in the estimated input data. Therefore, this study used a systematic approach, where the parameters of the input data were simulated to sequentially vary over the

Table 2. Basic events, reactive safety measures, and outcome events for BTA1

Category	Code	Description
Basic event	BE1–BE18	See Table 1
Safety measure	RSM1	Seatbelt
	RSM2	Guardrail
Outcome event	$OE1_{base}$	MAIS 1–3: minor to serious
	$OE2_{base}$	MAIS 3–5: serious to critical
	$OE3_{base}$	MAIS 4–6: severe to fatal
	$OE4_{base}$	MAIS 5–6: critical or fatal

Source: Data from Ehlers et al. (2017).

Table 3. Generated input data and literature knowledge at fuzzy scale for BTA1input events

Event	State (F or S)	TFN ($\mathbf{p_L}$, $\mathbf{p_m}$, $\mathbf{p_U}$)
BE1	F	(0.150, 0.275, 0.400)
BE2	F	(0.250, 0.388, 0.525)
BE3	F	(0.098, 0.199, 0.300)
BE4	F	(0.098, 0.199, 0.300)
BE5	F	(0.150, 0.275, 0.400)
BE6	F	(0.023, 0.074, 0.125)
BE7	F	(0.000, 0.025, 0.050)
BE8	F	(0.098, 0.199, 0.300)
BE9	F	(0.023, 0.074, 0.125)
BE10	F	(0.023, 0.074, 0.125)
BE11	F	(0.000, 0.025, 0.050)
BE12	F	(0.000, 0.025, 0.050)
BE13	F	(0.023, 0.074, 0.125)
BE14	F	(0.250, 0.388, 0.525)
BE15	F	(0.098, 0.199, 0.300)
BE16	F	(0.150, 0.275, 0.400)
BE17	F	(0.150, 0.275, 0.400)
BE18	F	(0.098, 0.199, 0.300)
RSM1	S	(0.230, 0.280, 0.330)
RSM2	S	(0.365, 0.455, 0.530)

Source: Data from Ehlers et al. (2017).
Note: BE = basic event; RSM = reactive safety measure; F = failure; S = success; and TFN = triangular fuzzy number.

entire range of event probabilities—from highly improbable to highly probable in linguistic terms. Thereby, the effect of changing input parameters on the analysis results could be studied and evaluated. This approach provided the lower and upper boundaries of the occurrence probability of a crash and its outcome events (consequences) when the parameters of the input events varied over the entire range of probability.

Case Studies 2 and 3: Simulated Variation in Expert Judgment on the Probability of Basic Events: Fault Tree

Although the input data of the base case should have been, and partially were, based on empirical knowledge, the additional four case studies were based on full-range expert opinions. In other words, instead of a specific and thus limited spectrum of expert judgment, the probability of all input events was simulated to sequentially vary from highly improbable to highly probable. This means that no data from expert acquisitions were used. Finally, the probability of the output events in the base case was compared with that in the other study cases, allowing a safety effect assessment of the new safety measures in addition to the traditional measures.

In Case Study 2 (BTA2), a cooperative proactive safety measure was applied in addition to the two traditional measures, as visualized in Crash Scenario 2. A local danger warning system was chosen as an example and was assumed to positively influence the probability of 6 of the 18 basic events: three driver-related and three road-related (Fig. 3). The occurrence probability of the other 12 basic events remained unchanged. A short description of the input and output events in this crash scenario is provided in Table 5. Theoretically, experts can be asked the following question to obtain their opinions on the effect of the chosen C-ITS on the probability of the 6 basic events: "Given a successful application of the stated proactive safety measure, how probable (likely) is it that this specific basic event, possibly in combination with other basic events, still occurs and initiates the crash?" However, instead of experts, linguistic terms now described the occurrence probability of the 6 basic events, covering the entire probability range, so the probability of the 6 basic events varied. The probability of the other basic events and the success probability of the reactive safety measures remained the same as in the base case (BTA1).

Fig. 5 shows the results for BTA2. The vertical lines represent the triangular fuzzy numbers (TFNs) of the likelihood of the event in question. The upper end of each line represents the upper boundary value of the TFN (the right value), and the lower end represents the lower boundary value (the left value). The actual data point, between the lower and upper boundary values, is the most likely probability value (i.e., the TFN modal value). The dotted horizontal lines represent the probabilities of the critical event (CE) and outcome events (OEs) in BTA1, with which the new probabilities in BTA2 are compared. The results show that the occurrence probability for all output events starts to decrease when the occurrence probability of the 6 basic events is estimated to be at least improbable. Further, a proactive safety measure that is estimated to increase the occurrence probability of the 6 basic events—compared with the base case—tends to slightly increase the likelihood of a crash and its outcome events.

In Case Study 3 (BTA3), linguistic terms were assigned to the probabilities of all basic events so that the probabilities could be simulated to vary from highly improbable to highly probable. This was supposed to simulate a full range of expert opinion on the effect of a cooperative proactive safety measure. In addition, the effect that varying probability of basic events has on quantitative bowtie analysis could be studied. Again, the success probability of the two traditional reactive safety measures, seat belt and guardrail, remained the same as in the base case (BTA1). Fig. 6 shows the results for BTA3, which reflect the results for BTA2. The probability of the critical event becomes 1 when the probability of all basic events is estimated as at least moderate. The results show that the likelihood of a crash and its outcome events decreases with the decreasing probability of the basic events. Further, a crash is almost unavoidable even if the probability of all basic events is estimated as very improbable. Only if the occurrence of all basic events is

Table 4. Calculated fuzzy probabilities for BTA1 output events

		Likelihood		
Reference	Description	Lower bound ($\mathbf{p_L}$)	Modal value ($\mathbf{p_m}$)	Upper bound ($\mathbf{p_U}$)
CE	Crash	0.839	0.977	0.998
$OE1_{base}$	Minor to serious injury	0.070	0.124	0.174
$OE2_{base}$	Serious to critical injury	0.091	0.149	0.209
$OE3_{base}$	Severe to fatal injury	0.205	0.320	0.407
$OE4_{base}$	Critical or fatal injury	0.264	0.383	0.488

Source: Data from Ehlers et al. (2017).
Note: CE = critical event; and OEx_{base} = outcome event from base case.

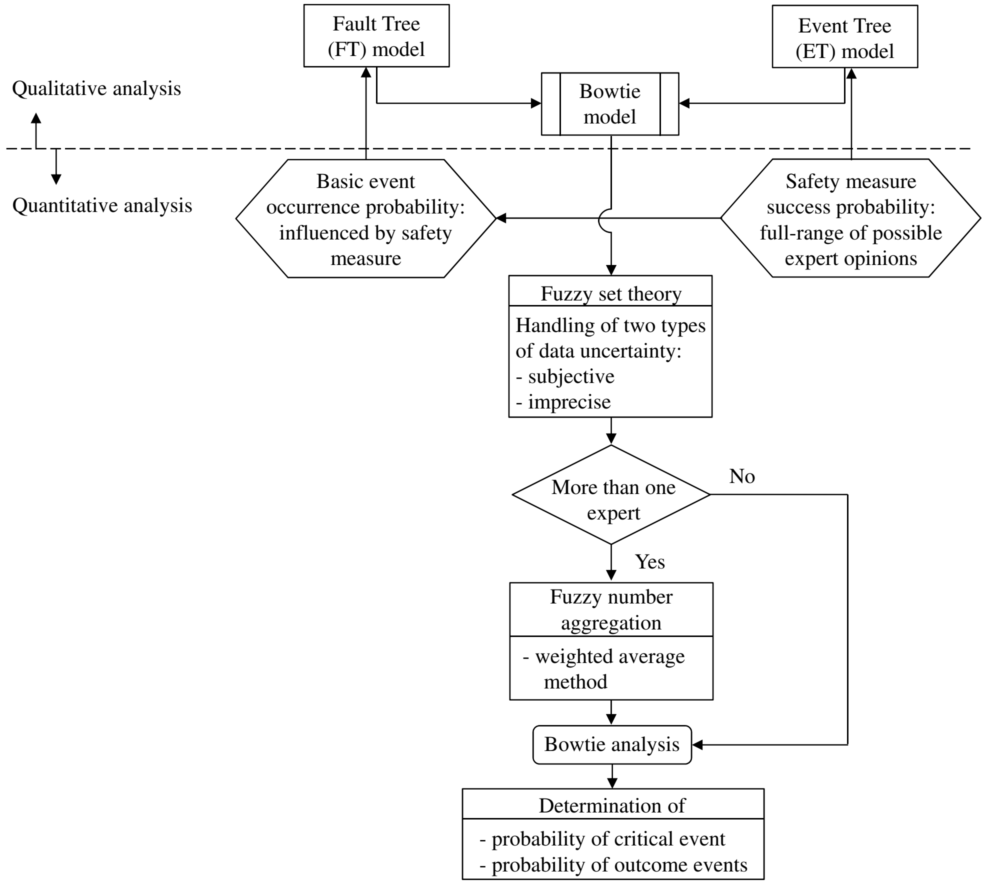

Fig. 4. Framework for bowtie analysis handling data uncertainty under full-range expert opinion. (Reprinted from *Accident Analysis and Prevention*, Vol. 99, Part A, U. C. Ehlers, E. O. Ryeng, E. McCormack, F. Khan, and S. Ehlers, "Assessing the safety effects of cooperative intelligent transport systems: A bowtie analysis approach," pp. 125-141, © 2017, with permission from Elsevier.)

Table 5. Basic events, reactive safety measures, and outcome events for additional cooperative system as proactive safety measure in BTA2

Category	Code	Description
Basic event	BE1–BE18	See Table 1
Safety measure	PSM1	Local danger warning system
	RSM1	Seat belt
	RSM2	Guardrail
Outcome event	OE1	MAIS 1–3: minor to serious
	OE2	MAIS 3–5: serious to critical
	OE3	MAIS 4–6: severe to fatal
	OE4	MAIS 5–6: critical or fatal

Source: Data from Ehlers et al. (2017).

estimated as highly improbable can the crash probability be reduced by more than half. The reason for this lies in the assumption made for the bowtie analyses: at least one factor occurs that initiates or contributes to a malfunction of the system leading to a crash. For example, the probability of the crash would be close to 1—even if the probability of all basic events except one were estimated as highly improbable—given that this one basic event would be estimated as highly probable. Again, the probability of a crash decreases with the decreasing probability of that one basic event.

An additional effect is found regarding the number of basic events and thus crash risk factors. If the number is reduced, the calculated likelihood of a crash is also reduced, which reflects the arithmetic in the bowtie model.

Case Studies 4 and 5: Simulated Variation in Expert Judgment on the Success Probability of the Reactive Safety Measures: Event Tree

In Case Study 4 (BTA4), variable linguistic terms were assigned to the success probability of the two traditional reactive safety measures, seat belt and guardrail. Although the actual success probability of these measures was taken from a credible report (Elvik et al. 2009), its effect on the output data when varied is of interest. The probability of all basic events remained the same as in the base case (BTA1), as did the bowtie diagram. The results show that, with highly ineffective reactive safety measures, a crash with a critical or fatal injury (OE4) is extremely likely (Fig. 7). In contrast, with highly effective safety measures, the outcome tends to be a minor to serious injury (OE1). This means that highly ineffective reactive safety measures worsen the outcome and vice versa. The probability of a crash producing a minor to serious injury increases with a decreasing probability of a crash producing a critical or fatal injury. If the success probability of all reactive safety measures were estimated as moderately probable, the probability would be the same for all outcome events.

In Case Study 5 (BTA5), the varying linguistic terms were assigned only to the estimated success probability of the cooperative reactive safety measure as illustrated in Crash Scenario 3. These linguistic terms were assumed to be expert opinions in response to the following question: "Given a crash in the defined settings, how probable (likely) is the success of the applied novel reactive safety measure?" Again, expert opinion was simulated to vary over

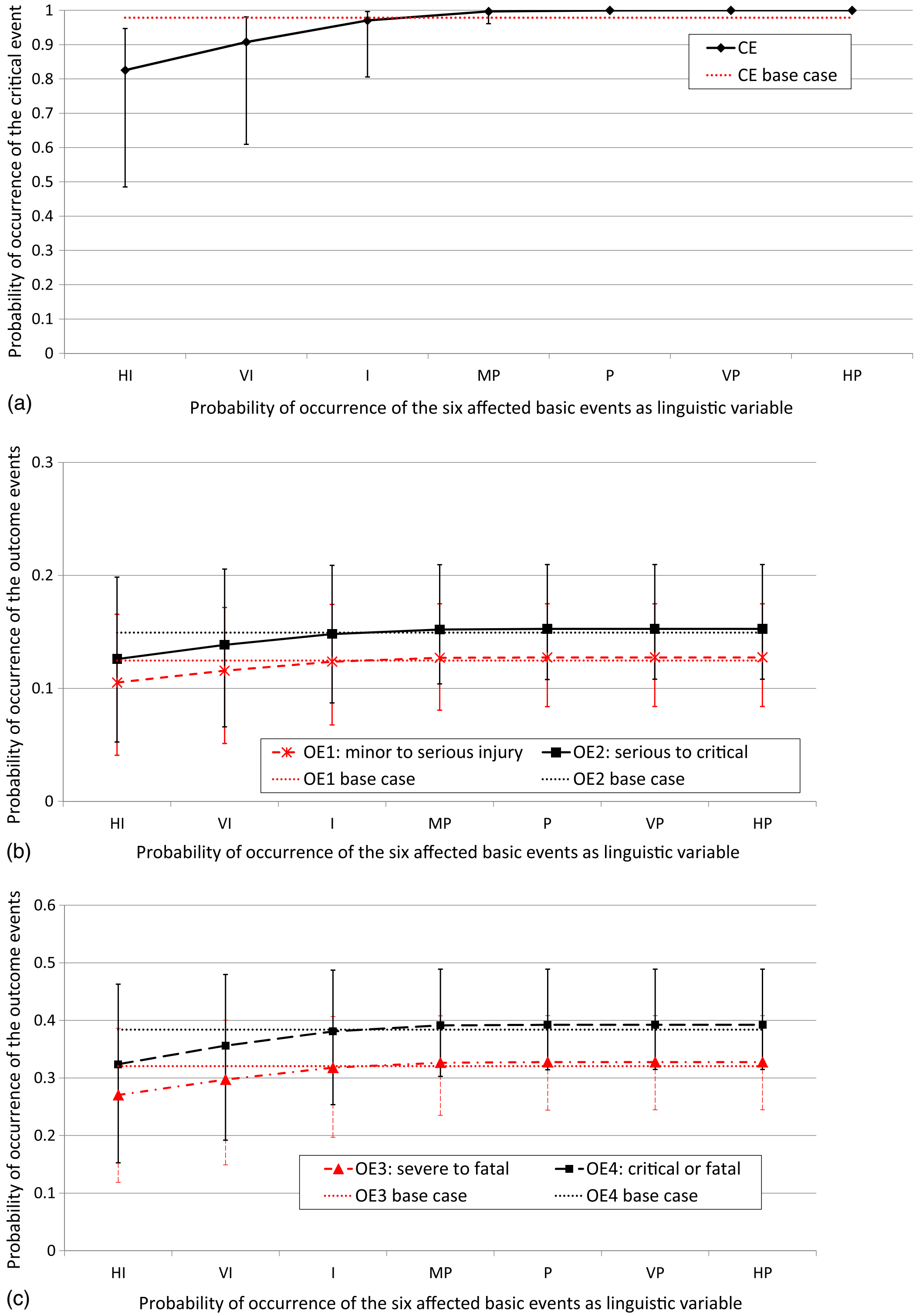

Fig. 5. Likelihood in BTA2 of (a) critical event (CE); (b) Outcome Events OE1 and OE2; and (c) Outcome Events OE3 and OE4 with simultaneously varying likelihood of the six basic events affected by the cooperative proactive safety measure in comparison with the base case.

the entire range of success probability. Chosen as a cooperative reactive measure was the emergency call system eCall, which automatically notifies the nearest emergency center immediately after the vehicle sensors detect a crash. Saving emergency response time and thus possibly lives is expected if all new cars are equipped with the eCall technology (EC 2016). The probability of the other input events remained the same as in BTA1. Fig. 8 shows the event tree for BTA5 with the cooperative eCall system as an additional reactive safety measure. Table 6 lists all events and measures involved. It was assumed that the eCall system affected neither the least nor the worst crash outcome.

Fig. 9 shows the results for BTA5 compared with the base case in BTA1. Fig. 10 shows the results for Outcome Events OE2–OE5 in detail. The probabilities of BTA1 are again plotted as horizontal

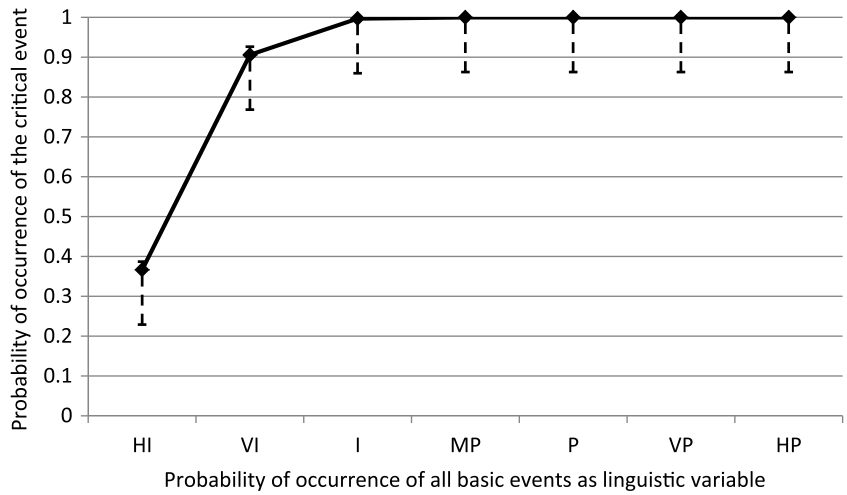

Fig. 6. Probability of critical event with varying likelihood of all basic events in BTA3.

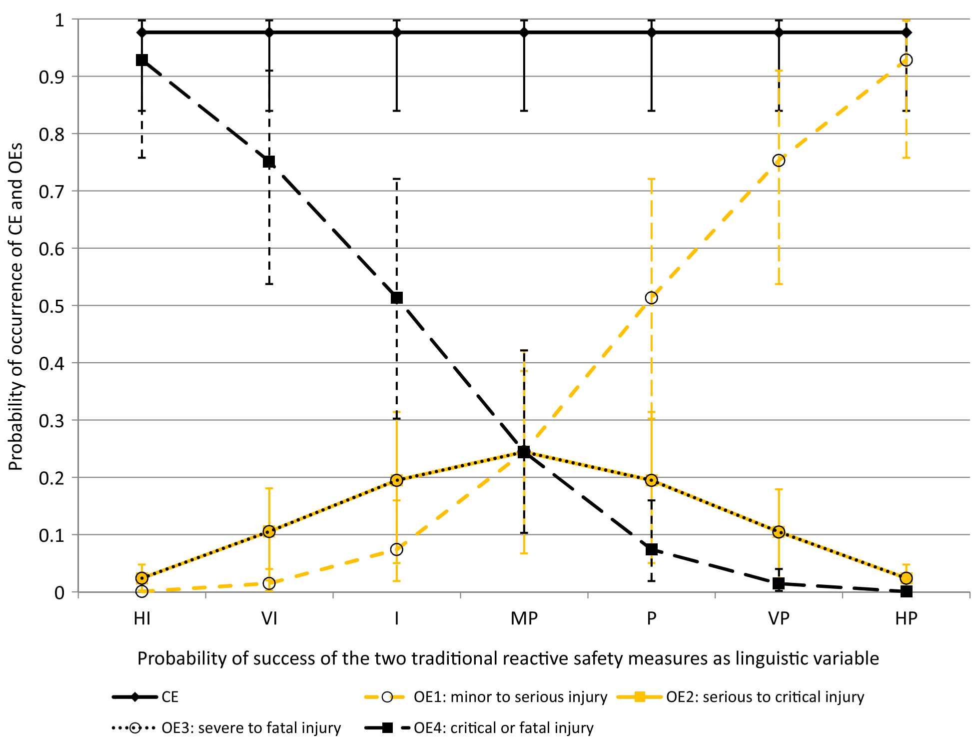

Fig. 7. Likelihood of critical event (CE) and outcome events (OEs) in BTA4 with varying success probability of the traditional reactive safety measures seat belt and guardrail.

dotted lines. The sum of the probabilities of OE2 and OE3 is equivalent to the probability of OE2 in the base case ($OE2_{base}$), as shown in Fig. 10(a). This is the result of the formulae used in the event tree analysis (the right side of the bowtie diagram) and the assumption that the least and worst outcome are not affected by the eCall system. The same is true for the sum of OE4 and OE5, being equivalent to the probability of OE3 in the base case ($OE3_{base}$), as shown in Fig. 10(b). The probability of the CE remains unchanged. The same applies to the probability of OE1 (minor to serious injury; MAIS 1–3), and OE6 (critical or fatal injury; MAIS 5–6). Thus, OE6 was the same as OE4 from the base case ($OE4_{base}$). However, the probability of the other outcomes changed depending on the estimated success probability of eCall. Both the probability of a serious to critical injury (OE3; formerly $OE2_{base}$) and the probability of a severe to fatal injury (OE5; formerly $OE3_{base}$) decrease with the increasing success likelihood of the additional safety measure. The success probability of the eCall system needs to be judged as at least "moderately probable" to reduce the probability of a serious to critical injury crash, as well as the probability of a severe to fatal injury crash, by half or more compared with the base case.

Discussion

There is a need for methods that assess the direct safety effects of emerging or future cooperative intelligent transport systems

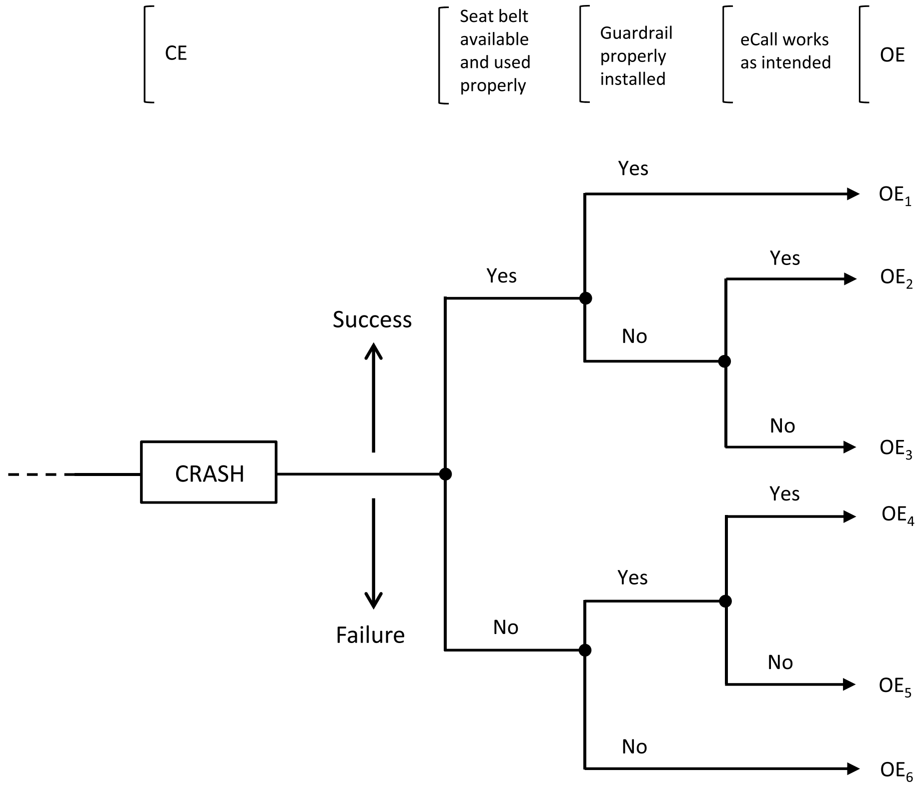

Fig. 8. Event tree for cooperative system as reactive safety measure in BTA5. (Reprinted from *Accident Analysis and Prevention*, Vol. 99, Part A, U. C. Ehlers, E. O. Ryeng, E. McCormack, F. Khan, and S. Ehlers, "Assessing the safety effects of cooperative intelligent transport systems: A bowtie analysis approach," pp. 125-141, © 2017, with permission from Elsevier.)

Table 6. Basic events, reactive safety measures, and outcome events for eCall system as additional reactive safety measure in BTA5

Category	Code	Description
Basic event	BE1–BE18	See Table 1
Safety measure	RSM1	Seat belt
	RSM2	Guardrail
	RSM3	eCall
Outcome event	OE1	MAIS 1-3: minor to serious
	OE2	MAIS 3-4: serious or severe
	OE3	MAIS 3-5: serous to critical
	OE4	MAIS 4-5: severe or critical
	OE5	MAIS 4-6: severe to fatal
	OE6	MAIS 5-6: critical or fatal

Source: Data from Ehlers et al. (2017).

(C-ITSs) in automotive or transportation engineering. To meet this need, Ehlers et al. (2017) proposed bowtie analysis. Bowtie analysis, which simulates varying expert judgment as proposed and demonstrated in this paper, allows estimating the safety effect of a specific safety measure independently of expert judgment. In other words, it simulates the entire range of possible expert answers (i.e., probabilities) by altering the input data that usually come from expert acquisitions, which are at risk for of bias and uncertainty. Fig. 11 is a flowchart of the proposed approach.

Under the assumptions in this study, the results for the second and third bowtie analyses (i.e., simulated variation in expert opinion on the probability of the basic events) suggest that (1) only proactive C-ITSs that decrease the probability of specific crash risk factors (those that represent the crash type in question) to at least very improbable can perceptibly decrease the probability of a crash. Otherwise, the crash is highly likely. Obviously, an ideal proactive C-ITS would decrease the probability of *all* basic events, and thus crash risk factors, to highly improbable, meaning that a crash is very likely to be prevented given (1) a proactive safety measure that informs and warns the driver about *all* potential driving errors, vehicle or infrastructure malfunctions, and environmental anomalies; and (2) prompt and adequate driver reaction to the received warning.

The bowtie model's arithmetic yields a decrease in the calculated likelihood of a crash with a decreasing number of basic events. This may suggest careful deliberation on whether highly improbable basic events need to be included in the final fault tree model. When two similar proactive C-ITSs are to be compared, the more basic events positively influenced, the better. This means that the system that most decreases the probability of the basic events qualitatively and quantitatively will have the greatest safety effects.

The results for the fourth and fifth bowtie analyses (i.e., simulated variation in expert opinion on the success probability of the reactive safety measure) indicate that, under the assumptions in this study, the probability of a serious to critical injury crash and that of a severe to fatal injury crash can be reduced by half or more if the success probability of the chosen reactive C-ITS eCall is estimated as at least moderately probable. In fact, any additional reactive safety measure positively affects crash outcomes because it yields an even more fragmented classification of injury severity, given that it works as assumed in the qualitative consequence analysis.

Bowtie analysis has a limitation that is apparent when applied to transportation safety: the assumption of statistical independence between input factors. In real life, interdependence and correlations between crash risk factors are evident. Further, crash risk factors are known to influence crash outcomes. In bowtie analysis, the

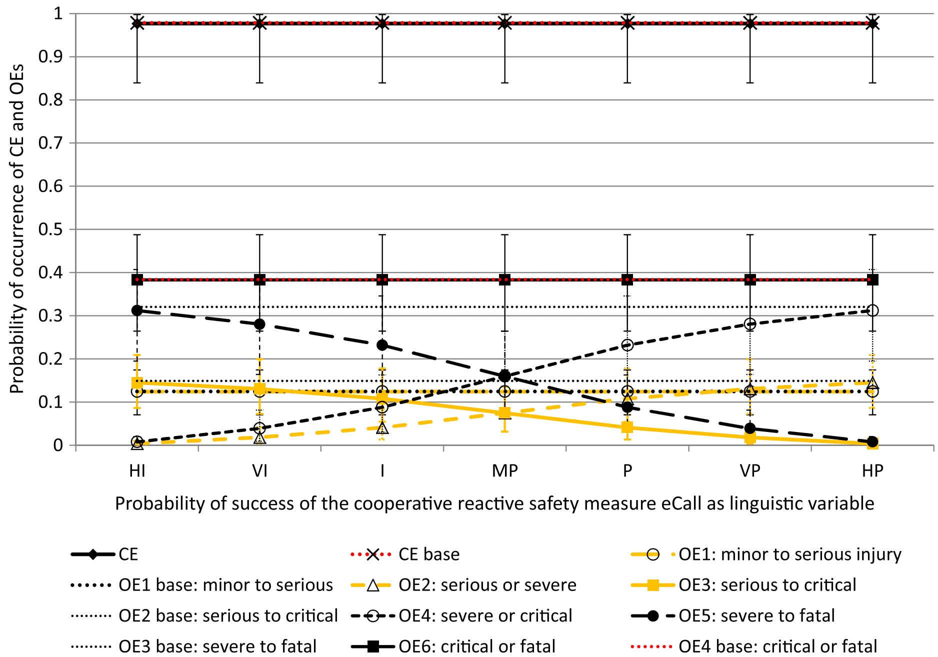

Fig. 9. Likelihood of critical event (CE) and outcome events (OEs) in BTA5 with varying estimated success probability of cooperative reactive safety measure eCall in comparison with the base case. CE base = critical event from base case; OE*x* base = outcome event from base case.

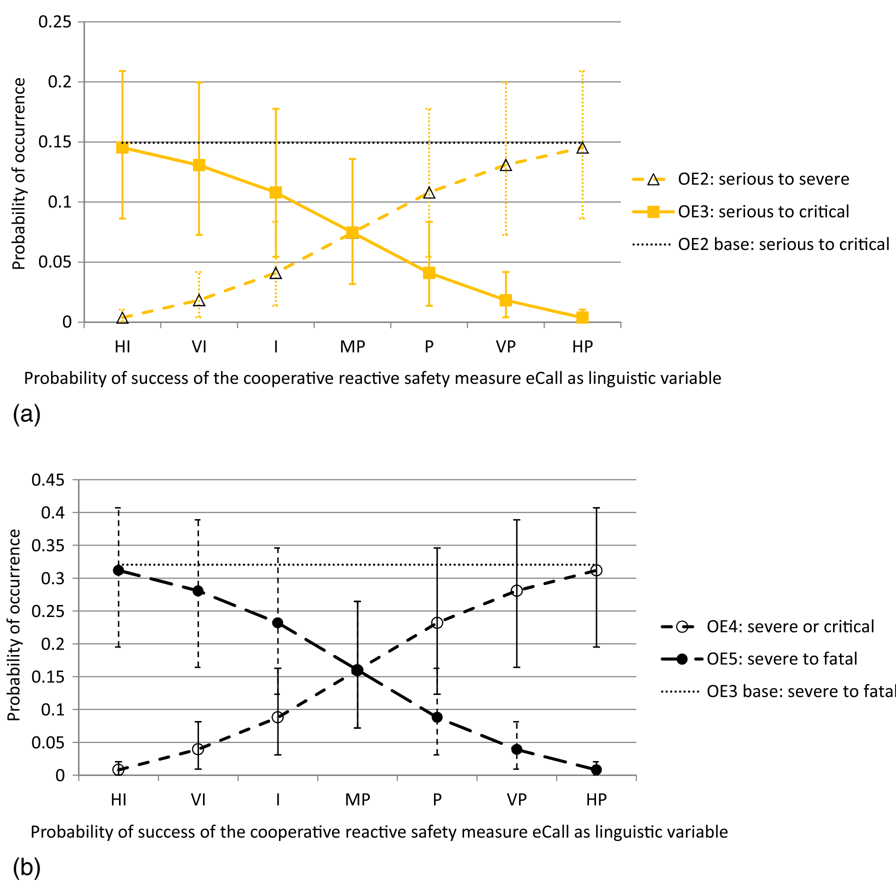

Fig. 10. Likelihood in BTA5 of (a) Outcome Events OE2 and OE3; and (b) Outcome Events OE4 and OE5 with varying estimated success probability of eCall in comparison with the base case. OE*x* base = outcome event from base case.

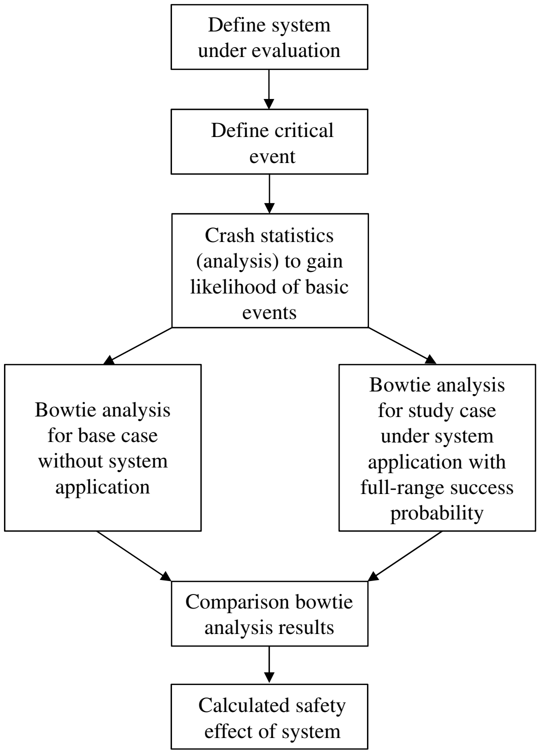

Fig. 11. Flowchart of proposed bowtie approach without expert acquisition.

probability of the risk factors (i.e., basic events) is considered only in the calculation of critical event probability, not in the calculation of outcome events. Moreover, direct effects of emerging technologies on driver behavior are still unknown and thus involve high uncertainty. For these reasons, bowtie analysis may be criticized as oversimplifying dynamic and complex crash behavior and crash consequences. However, models typically simplify reality in order to allow problem solving, which naturally includes model uncertainty.

Other limitations and uncertainties may concern the empirical crash data used in the bowtie model for safety effect estimation. These may involve variations and incomplete information. Evidently, an increase in input data accuracy strongly improves the quality of model output—the safety effect estimations. Bayesian analyses are one way to model these uncertainties. Through automatized big data collection, it might be possible to precisely quantify the probability of all crash risk factors in the future, taking into account their interrelations and variations. Bowtie analysis can be used for this purpose, as it allows for dynamic updates of input parameters given new evidence (e.g., Ferdous et al. 2012; Paltrinieri et al. 2013). Overall, crash models can be expected to become more accurate and should eventually allow the modeling of dynamic processes and interdependencies, including human behavior.

Conclusion

This paper demonstrated an upgraded bowtie approach in a semiquantitative assessment of emerging safety measures for transportation safety. Four case studies using bowtie analyses were described whose input parameters sequentially varied over the entire range of possible expert answers. These results were compared with the results for an initial base case study whose input data were partially generated as examples and partially based on existing knowledge. This allowed the identification of (1) the sensitivity of the probability of a crash and its consequences (output data) to the entire spectrum of expert judgment used in the bowtie model and (2) the necessary safety effectiveness of a chosen C-ITS allowing adequate changes in the probability of a crash and its consequences.

Whereas the bowtie approach has the limitation of assuming independence between input parameters, it allows for a practical assessment of C-ITSs and their safety effects necessary to achieve adequate changes in the probability of crashes and their consequences. Using this method, decision makers such as road authorities can identify the minimum safety effectiveness to be achieved by C-ITSs or other future safety measures, and they can then choose the best investments to support safety. The upgraded bowtie approach demonstrated in this study allows assessments without expert data acquisitions, which are usually at risk for uncertainty and bias. Yet it makes possible purposeful communication and interpretation of the potential effects of safety measures. Future research may address the limitations of bowtie analysis such as the assumed independence among input events. For example, a dependency coefficient can explore different kinds of interdependence. An additional sensitivity analysis can determine the most significant contributing input events for the output events. This may support the final selection of basic events for the bowtie model.

Acknowledgments

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