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On the importance of driver models for the development and assessment of active safety: A new collision warning system to make overtaking cyclists safer

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ABSTRACT

The total number of road crashes in Europe is decreasing, but the number of crashes involving cyclists is not decreasing at the same rate. When cars and bicycles share the same lane, cars typically need to overtake them, creating dangerous conflicts—especially on rural roads, where cars travel much faster than cyclists. In order to protect cyclists, advanced driver assistance systems (ADAS) are being developed and introduced to the market. One of them is a forward collision warning (FCW) system that helps prevent rear-end crashes by identifying and alerting drivers of threats ahead.

The objective of this study is to assess the relative safety benefit of a behaviour-based (BB) FCW system that protects cyclists in a car–to–cyclist overtaking scenario. Virtual safety assessments were performed on crashes derived from naturalistic driving data. A series of driver response models was used to simulate different driver reactions to the warning. Crash frequency in conjunction with an injury risk model was used to estimate the risk of cyclist injury and fatality.

The virtual safety assessment estimated that, compared to no FCW, the BB FCW could reduce cyclists' fatalities by 53–96% and serious injuries by 43–94%, depending on the driver response model. The shorter the driver's reaction time and the larger the driver's deceleration, the greater the benefits of the FCW. The BB FCW also proved to be more effective than a reference FCW based on the Euro NCAP standard test protocol. The findings of this study demonstrate the BB FCW's great potential to avoid crashes and reduce injuries in car–to–cyclist overtaking scenarios, even when the driver response model did not exceed a comfortable rate of deceleration. The results suggest that a driver behaviour model integrated into ADAS collision threat algorithms can provide substantial safety benefits.

1. Introduction

According to the Global Status Report 2018 from the World Health Organization, vulnerable road users (VRU), such as pedestrians and cyclists, constitute 26% of road traffic deaths (WHO, 2018). In Sweden in 2017, 84% of the severe–to–fatal bicycle crashes reported by the police were collisions with motor vehicles, of which 70% were car–to–cyclist collisions (Trafikverket, 2020). Most of these crashes occur at intersections or in situations where the car and the bicycle share the road and are going in the same direction (Isaksson-Hellman & Werneke, 2017; Wisch et al., 2017). Similar findings have been reported in several studies using different crash databases across different countries. The analyses of data from several countries (France, Germany, Italy, Netherlands, Sweden, and UK) all show that the most prevalent scenario is that in which the cyclist crosses the road in an approximately perpendicular direction towards the passenger car (Op den Camp, Ranjbar, Uittenbogaard, Rosen, & Buijssen, 2014). Longitudinal scenarios in which the car and the cyclist travel in the same direction and the cyclist is impacted from behind by the car also comprise a substantial portion of car-to-cyclist crashes. More specifically, these longitudinal scenarios account for 10–49% of all fatal crashes between cars and bicyclists; for crashes with serious injuries, they account for 7–29%. (The exact percentages depend on the country). For France, Germany, and Sweden, in the longitudinal scenarios, 40–50% of the crashes with serious injuries and 75–85% of the fatal crashes occurred in rural areas and on straight roads (Uittenbogaard et al., 2016a; Fredriksson et al.,

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2014; Uittenbogaard et al., 2016b). The longitudinal scenarios made up the largest share (ranging from 25 to 64%) of cyclist fatalities in car-to-cyclist crashes in Germany, Hungary, and Sweden; the high fatality rates were linked to the higher car impact speeds observed on rural roads (Wisch et al., 2017). In Japan, the longitudinal scenarios represent approximately 8% of all car-to-cyclist crashes and 48% of fatal car-to-cyclist crashes (ITARDA, 2018). In the US, longitudinal scenarios represented approximately 9% of all car-to-cyclist crashes and 11% of those crashes which resulted in injury, but 45% of fatal car-to-cyclist crashes, according to MacAlister and Zuby (2015). The MacAlister and Zuby (2015) study further showed that the speed limit was greater than 64 km/h in 74% of the longitudinal-scenario fatal crashes. Furthermore, Uittenbogaard et al. (2016a) reported that both fatal crashes and crashes with serious injuries in the longitudinal car-to-cyclist scenarios typically occur on roads with a higher speed limit than other crash scenarios (i.e., 40–85% of the longitudinal scenarios occurred on roads with a speed limit of 70–90 km/h). They further found that the initial vehicle speed was approximately 40–45 km/h and 70–80 km/h for the 50th and 90th percentiles, respectively (Uittenbogaard et al., 2016a). Similarly, a study by Kuehn et al. (2015) reported 51 km/h. The initial cyclist speed, for both fatalities and serious injuries, was about 15 km/h and 20–25 km/h for the 50th and 90th percentiles, respectively (Uittenbogaard et al., 2016a). The fatal crashes occurred at higher initial vehicle speeds than the crashes with seriously injured cyclists, while the cyclist speed was not shown to influence the severity level (Uittenbogaard et al., 2016a). A few studies have reported the actual speed of the car at the time of collision in this scenario, although the results were not separated by road type. For example, Lindman et al. (2015) reported that the car's average collision speed was 44 km/h, and Kovaceva et al. (2018a) reported that it was 43 km/h (with a range of 10–80 km/h). The cyclist's average speed at collision was 15 km/h, similar to the cyclist's initial speed (Kovaceva et al., 2018a).

In summary, although car–to–cyclist collisions are more frequent in crossing situations, the risk of a severe–to–fatal injury is significantly higher for collisions in the same–direction situation (Isaksson-Hellman & Werneke, 2017; Wisch et al., 2017). When cars and cyclists share the same lane, cars typically need to overtake cyclists, creating dangerous conflicts—especially on rural roads, where cars travel much faster than cyclists. Collisions with large speed differences often result in severe injuries or even fatalities. Preventing same-direction collisions with vehicles or mitigating their violence would greatly reduce the number of cyclist fatalities and severe injuries.

Advanced driver assistance systems (ADAS) have the potential to reduce the number of these collisions and mitigate their outcomes. As an example, forward collision warning (FCW) systems are implemented in modern vehicles to warn the driver (with a visual, auditory, or tactile cue) when a collision with a leading vehicle is imminent. FCW systems are usually designed to warn the driver as close in time to the collision as possible, so that the warning does not activate if the driver can still avoid the collision with a corrective manoeuvre. Improved FCWs that can detect and signal a pending collision with a cyclist are being developed and are expected to penetrate the market in the near future; it is important to quantify and optimise the expected safety benefit before then. The European New Car Assessment Program (Euro NCAP) has recently started to assess cyclist FCW systems (Euro NCAP, 2019).

So far, safety benefit of ADAS has been assessed, in general, *retrospectively* and *prospectively*. A retrospective assessment is based on observed real-world data after the systems are available in vehicles (Cicchino, 2017; Doyle, Edwards, & Avery, 2015; Isaksson-Hellman & Lindman, 2016; Kuehn, Hummel, & Bende, 2009). For evaluating new systems that are not yet on the market, a prospective assessment may be performed virtually (see, for example, Page et al. (2015)). In a virtual assessment, often taking the form of *counterfactual simulations,* a reanalysis of real-world data (crashes or near-crashes) is typically performed (Alvarez et al., 2017; Bärgman, Lisovskaja, Victor, Flannagan, & Dozza, 2015; Sander, 2018). These simulations assess the extent to which a new safety system (for instance, an FCW) would be able to reduce the number and/or severity of crashes. The real-world data typically used as input provide *baseline* events, without the ADAS under assessment (Alvarez et al., 2017). The baseline events can be derived from real-world crash events (Kusano and Gabler, 2012; Lindman et al., 2010; Sander and Lubbe, 2016) or modified real-world events (Bärgman et al., 2017a; McLaughlin et al., 2008; Seacrist et al., 2020). The crash events are typically reconstructed from in-depth crash databases (Chajmowicz, Saadé, & Cuny, 2019; Char, Serre, Compigne, & Guillen, 2020; Lindman et al., 2010). In contrast, the modified real-world events may also use safety–critical events (e.g., crashes and near-crashes) from naturalistic driving (ND) data (Bärgman et al., 2017a; McLaughlin et al., 2008; Seacrist et al., 2020; Victor et al., 2015; Zhao, Ito, & Mizuno, 2019). The advantage of ND data is that everyday driving behaviour with vehicle kinematics and the interactive behaviour of road users, can be observed. This information is usually not available in in-depth reconstructed crash data, which are typically reconstructed for the road users involved in the crash or for stationary objects. The dynamic surroundings, such as other moving road users interacting with the road users involved in the crash, are often missing (Erbsmehl, 2009). Furthermore, the usual procedures for reconstructing crashes (e.g., on-site investigation, or retrospective investigation based on court cases) are difficult to apply in collisions when one of the involved road users is a VRU. There are several reasons for this (Bakker et al., 2017; Barrow et al., 2018; Dekra, 2020; Simms & Wood, 2009). First, it is often impossible to determine the exact location of the collision, as the involved road users may have cleared the area by the time the police (or the crash investigation team) arrive. Second, the final relative positions of the road users involved in the collision are difficult to assess, since there are rarely tire marks or other indications showing precisely where the cyclist travelled (the cyclist may have ridden on the road, mixed road/bicycle path, or bicycle path). If the final position cannot be identified exactly, then the final position of the bicycle is based on witness statements or interviews with the road user (if the crash was not fatal). Third, a calculation of the collision speed, which is based on the damage to the vehicles, is often impossible for collisions involving bicycles, due to the bicycle's relatively low speed; impacted structures are rarely deformed. As a result, it is difficult to know how accurate in-depth crash databases from reconstructions are (Bakker et al., 2017; Barrow et al., 2018; Dekra, 2020).

When detailed information about the pre-crash road user kinematics is limited, as is the case in car-to-cyclist collisions, complementary information, such as car and cyclist trajectories and cyclist speeds, can be retrieved from ND studies (Fitch & Hanowski, 2012). Several large-scale ND studies have been conducted to date, such as SHRP2 (Hankey, Perez, & McClafferty, 2016; SHRP2 TRB, 2015), which is the largest in the world, UDRIVE, which is the largest in Europe (van Nes, Bärgman, Christoph, & van Schagen, 2019), and CNDS in Canada (Harbluk et al., 2018). However, very few car-to-cyclist crashes are available for analysis. For example, in SHRP2, 65 events (three crashes and 62 near-crashes) were categorised as vehicle-cyclist conflicts, of which 10% were car-to-cyclist longitudinal rear-end interactions (Haus & Gabler, 2018). In CNDS, out of 83 crashes with the instrumented passenger vehicles, 2% were crashes with pedestrian and pedelecs—in which no separation has been made for car-to-cyclist crashes (Harbluk et al., 2018). In the UDRIVE study, no car-to-cyclist crashes were reported (Ehsani et al., 2021; van Nes et al., 2019). Other studies have been conducted in which the required real-world crash data were not available, or the quality of the crash parameters was not sufficient. In these studies, crash data were extrapolated from ND data, such as near-crashes and everyday driving, but no crashes. Many researchers, such as Woodrooffe et al. (2012, 2013a), McLaughlin et al. (2008), Fitch and Hanowski (2012), and Bärgman et al. (2017a), have argued that such data are useful for the design, testing, and evaluation of ADAS.

In counterfactual simulations, the assessment of the safety benefit of FCW systems has mainly focussed on car–to–car crashes (Bärgman et al.,

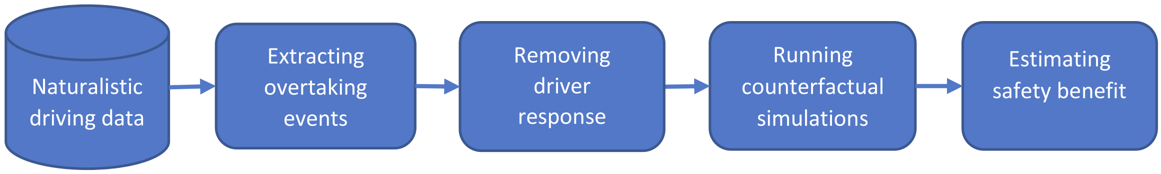

Fig. 1. Methodology overview for safety benefit estimation of FCW for car–to–cyclist crash avoidance in overtaking manoeuvres.

2017a; Kusano & Gabler, 2012). However, some attempts have been made to assess the safety benefit of FCW for car–to–cyclist crashes. Recently, theoretical FCW systems with different sensor parameters were assessed for car–to–cyclist crashes (Char et al., 2020). However, that study examined only the reduction in number of crashes, not the reduction in cyclists' injuries. Other recent research highlights that not only improved sensor parameters, but also the inclusion of driver behaviour models in the FCW systems, may be crucial to improve the intervention timing, which in turn may increase FCW effectiveness (Dozza, Schindler, Bianchi Piccinini, & Karlsson, 2016; Lubbe & Davidsson, 2015). A behaviour-based (BB) FCW system which uses a novel driver behaviour model (Rasch & Dozza, 2020) in the collision threat algorithm (Thalya, Lubbe, Knauss, & Dozza, 2020) has been designed for car-overtaking-cyclist scenarios. This system takes into account the interaction between a cyclist and an oncoming vehicle, when present (Thalya et al., 2020). The safety benefit of this BB FCW system has, however, not yet been assessed.

The safety benefit of FCW, in terms of avoided crashes, depends on the driver's response to the warning. Thus it is unsurprising that the choice of driver response model in counterfactual simulations has a large effect (Bärgman et al., 2017a). A driver response model can include the driver's reaction time or a model thereof (Markkula, Engström, Lodin, Bärgman, & Victor, 2016) and the driver's evasive manoeuvre (e.g., braking) or a model thereof.

Driver reaction time is defined as the time from the event (e.g., lead vehicle braking or onset of an FCW) to when the driver applies the brakes (M. Green, 2000; SAE International, 2015; Sivak, Olson, & Farmer, 1982). Numerous studies have measured the influence of FCW on the driver reaction time in car-to-car rear-end scenarios (for reviews, see Campbell et al., 2007; Green et al., 2008). A common approach in these studies, usually performed in a simulator, is to compare the average driver reaction times with and without FCW when the driver is exposed to a critical lead-vehicle braking event (Abe & Richardson, 2005, 2006; Bueno, Fabrigoule, Ndiaye, & Fort, 2014; J. D. Lee, McGehee, Brown, & Reyes, 2002; Scott & Gray, 2008). Previous research has shown the FCW's ability to speed up the driver response process (Bueno et al., 2014; J. D. Lee et al., 2002; Ljung Aust, Engström, & Viström, 2013; Scott & Gray, 2008). The mean reaction times for car-to-car rear-end scenarios in several studies, which investigated different conditions, varied from 0.623 s to 2.11 s (Abe & Richardson, 2005; J. D. Lee et al., 2002; Lylykangas et al., 2016; Yue et al., 2021). After the driver has started braking, the braking manoeuvre may be represented by a braking profile which includes the maximum deceleration (Brach, 2005; Lechner & Ferrandez, 1990) and the jerk required to reach the maximum deceleration (Brännström, Coelingh, & Sjöberg, 2014). Both controlled and naturalistic studies have reported that drivers will brake progressively harder until they reach a certain deceleration (Fambro et al., 2000; J. D. Lee et al., 2002), which is often close to the vehicle limits given the specific road conditions (Fambro, Koppa, Picha, & Fitzpatrick, 2000; J. D. Lee, McGehee, Brown, & Marshall, 2006; Mcgehee, 1999). Furthermore, Markkula et al. (2016) show that the braking profile (typically a piecewise linear function of the deceleration) appears to be a good fit for data from real-world crashes and near-crashes. These three parameters, driver brake reaction time, brake deceleration, and jerk, are particularly crucial in the assessment of FCW's collision reduction (Brown, Lee, & McGehee, 2001; Haus, Sherony, & Gabler, 2019; Kusano & Gabler, 2012; McLaughlin et al., 2008; Woodrooffe et al., 2013b). However, ensuring that these parameters accurately reflect driver behaviour in car-to-cyclist interactions is challenging because real-world data are sparse. Previous studies addressing the influence of drivers' responses to the FCW on crash avoidance have focussed mostly on rear–end car–to–car crashes (Bärgman et al., 2017a; Koustanaï, Cavallo, Delhomme, & Mas, 2012; Wu, Boyle, & Marshall, 2017). Some car-to-cyclist driver response models have been derived, albeit mainly for crossing scenarios (Boda, Lehtonen, & Dozza, 2019). Although a recent study by Aderum et al. (2020) describes the driver response process when overtaking cyclists on rural roads in a naturalistic setting, a quantitative model for this scenario has not yet been developed. The effect of the driver's response model on the effectiveness of FCW for car–to–cyclist overtaking crashes has not previously been estimated.

The aim of this study is to assess the safety benefit of a recently developed BB FCW system (Thalya et al., 2020) that protects cyclists as drivers approach to overtake them, using the same baseline data to compare the safety benefits of the BB FCW and a reference system. The comparison is made using counterfactual simulations based on crashes derived from ND data. Each derived crash was simulated under three different conditions: the vehicle was equipped with the BB FCW, a reference FCW, or no FCW. Different driver response models, expressed through different values of the three parameters, have established precedents in previous research (Bärgman et al., 2017a; Brännström et al., 2014; Haus, Anderson, Sherony, & Gabler, 2021; Kusano & Gabler, 2011; Woodrooffe et al., 2013a). Each model was implemented for each condition, providing a sensitivity analysis of the two FCWs by demonstrating the differences in safety benefits with different driver response model parameters. The safety benefits were assessed by estimating the reduction in the number of crashes, the crashes' severity, and cyclists' injury risks.

2. Method

An overview of our methodology is shown in Fig. 1. This methodology used vehicle time-series data from car–to–cyclist overtaking events extracted from ND data (Bärgman et al., 2017b). These events included normal driving situations in which the driver did not impact the cyclist. The events were modified by removing the drivers' responses (e.g., steering or braking) to simulate situations in which the drivers did not steer or brake because, for example, they were inattentive and failed to see the cyclist. All of the modified events, with no FCW, resulted in rear–end collisions with the cyclist. The counterfactual simulations applied the FCW systems to these events. The system warning would trigger a driver reaction as the vehicle got closer to the cyclist, helping the driver avoid the rear–end collision. The safety benefit of the system (in terms of the injury risk—number of lives saved and the reduction in injuries) was estimated from the output of the simulations: the number of avoided or mitigated (i.e., reduced-collision-speed) crashes.

2.1. Extracting overtaking events from naturalistic driving data

Overtaking events in which a car driver overtakes a single bicyclist on a straight rural road were extracted from the ND data, collected in France for the UDRIVE project (Bärgman et al., 2017b). A data acquisition system (DAS) was installed in the vehicles, registering seven camera views (front left, front centre, front right, cabin view, cockpit

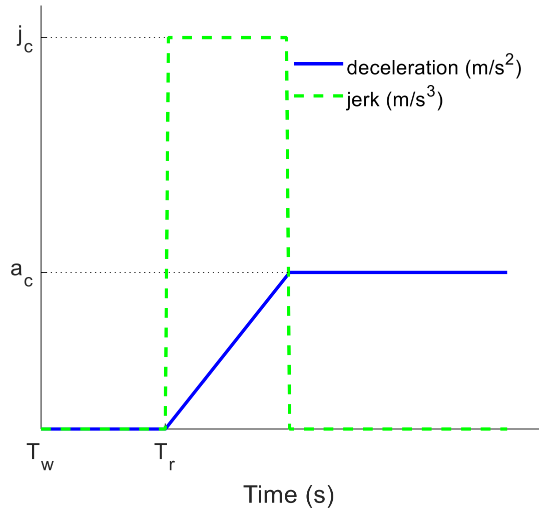

Fig. 2. Driver braking profile, where T_w is the warning activation time, T_r is the driver reaction time, a_c is the constant deceleration, and j_c is the constant jerk.

view, driver face, and pedals), CAN bus data (e.g., vehicle speed, acceleration, steering wheel angle, and yaw rate), and GPS position (enriched through map matching). Furthermore, the DAS also recorded continuous signals from a smart camera system, MobilEye (Shashua et al., 2004), which included information about the presence of cyclists and their position (lateral and longitudinal) relative to the instrumented vehicle. The details about the identification of the overtaking manoeuvres in the ND data are described in Kovaceva et al. (2018b); a summary is provided in the Appendix. Each of the events was divided into four overtaking phases in accordance with Dozza et al. (2016) and Kovaceva et al. (2018b). In this study, we analysed the data from the first two phases, approaching and steering away.

2.2. Removing driver response

In order to investigate what would happen if the driver did not steer or brake (for instance, because of failure to see the cyclist), the events were counterfactually modified. That is, the driver's response to the presence of a cyclist ahead and the resulting vehicle kinematics were removed from the data. Thus, each counterfactual event maintained the drivers' lateral position and speed at the onset of the original response manoeuvre, which occurred during the approaching phase. The point in time when the driver responded (braked or steered) is hereafter called the response point. For the events in which drivers *braked* during the approaching phase, the brake onset was identified from the brake pedal signal (brake pedal pressed). Then, from that time, the speed was kept constant (Bärgman et al., 2017a). For the events in which drivers *steered* at the end of the approaching phase, the steering away onset was identified by video annotations (Kovaceva et al., 2018b). In these events, the driver's steering response was removed; the drivers were assumed to keep the same lane position until they crashed with the cyclist.

The counterfactual event kept the cyclist's (and the oncoming vehicle's, when present) actual time-series data up to the driver's response point, after which they were assumed to maintain the same lateral position and speed. After this procedure, all extracted overtaking events resulted in rear–end crashes (the car impacted the cyclist). These crash events were then used as baseline events, without FCW; the two FCW systems under assessment were applied to them through counterfactual simulations. The differences in outcome (number of avoided crashes, collision speed, injury risk and lives saved) were compared for the three sets of events.

2.3. Running counterfactual simulations

The input to each counterfactual simulation was a vector of measurements (from the start of the approaching phase to the time of the crash) including 1) the longitudinal distances between the vehicle and the cyclist and the vehicle and any oncoming vehicle, 2) the lateral distance between the cyclist and any oncoming vehicle, and 3) the speeds, positions, and headings of both the vehicle and the cyclist. This input was then processed by the FCW system under assessment. The FCW computed an output binary signal that indicated the status of the warning to the driver (on or off) over time. The driver reaction to the warning, simulated according to different driver response models (fully reported below), set an acceleration output which was then integrated to calculate the future speed and position of the vehicle. If the vehicle stopped before reaching the cyclist (i.e., the distance between the vehicle and the cyclist was greater than zero) then the crash was avoided; otherwise, the crash remained, and the collision speed was recorded.

2.4. Collision warning systems

The two FCW systems examined were: a reference FCW based on the EuroNCAP protocol for ADAS for VRU testing (Euro NCAP, 2019) and a BB FCW first presented in Thalya et al. (2020). Applying these two FCW systems to the same baseline events allowed us to compare the estimated safety benefits that each system could offer.

The algorithms that are responsible for the activation of a commercial FCW system usually depend on the manufacturer and are often secret. However, a simple metric that has been generally used to judge the collision threat is time to collision (TTC) (Jansson, 2005; Kiefer, Flannagan, & Jerome, 2006; van der Horst & Hogema, 1993). In this study TTC is defined as the ratio of the distance between car and cyclist and their relative speed. Recently, the Euro NCAP started testing FCW systems in rear–end scenarios with cyclists and rewarding systems that activate before the TTC to the cyclist becomes 1.7 s (Euro NCAP, 2019). This simple threshold was used to define the reference FCW in this paper: the system calculates the TTC and issues a warning at TTC = 1.7 s.

The BB FCW, on the other hand, is not triggered by a TTC value; instead, it is triggered by a collision threat algorithm, which integrates a driver behaviour model recently developed specifically to improve the timing of the warning (see the flow chart of the BB FCW in the Appendix). The model predicts the probability that the driver will brake and/or steer as the driver approaches the cyclist. As the probability gets higher, a mismatch between the behaviour model's prediction and the driver's actual braking and steering actions (as measured from the vehicle network) generates a threat. The threat leads to a decision about whether to trigger a warning, according to a threshold-based strategy. The threshold is an upper limit—the highest acceptable probability (0.9, for example) before a warning is issued. This threshold is set by the system designer to optimize the true positive activation rate by trying to ensure that the warning occurs outside the comfort zone of most drivers. The concept of driver comfort zones explains that drivers minimize their risk by choosing to stay far enough away from potential hazards to feel safe and comfortable (see Summala (2007) for a full description). Once drivers exceed their comfort zone boundary, they experience a feeling of discomfort, which is likely to justify a system intervention such as FCW (Ljung Aust & Engström, 2011). In the ideal collision threat algorithm, the model's threshold is exceeded (and the warning is triggered) just after the driver's comfort boundary has also been exceeded. Thus, the balance of driver acceptability and time to avoid a crash is optimized. Detailed descriptions of the driver behaviour model and the BB FCW can be found in Rasch et al. (2020) and Thalya et al. (2020), respectively.

2.5. Modelling driver response input

The effectiveness of an FCW largely depends on the response of the

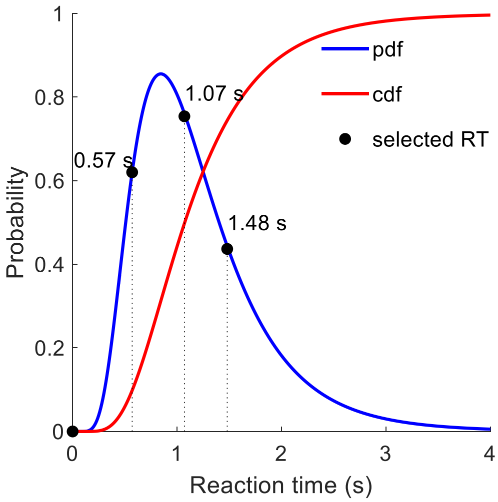

Fig. 3. Probability density function (pdf, in blue), cumulative probability density function (cdf, in red) of driver reaction times from Sivak et al (1982) and the selected reaction times (RT) for the counterfactual simulations. The selected RTs 0.57 s, 1.07 s, 1.48 s represent 10%, 50%, and 75% of the driver reaction times, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Driver response models with the model parameters.

Driver response model	Reaction time (s)	Braking profile Deceleration (m/s^2)	Jerk (m/s^3)
Without RT-C	0	4	10
Fast-C	0.57	4	10
Medium-C	1.07	4	10
Slow-C	1.48	4	10
Without RT-M	0	6.79	26.14
Fast-M	0.57	6.79	26.14
Medium-M	1.07	6.79	26.14
Slow-M	1.48	6.79	26.14

driver to the warning. In this paper, we use two different types of driver models. The first type of model is the driver behaviour model by Rasch et al. (2020) that predicts the probability that the driver will brake or steer as the driver approaches the cyclist. This model, based on driver comfort zone boundaries, was included in the BB FCW algorithm by Thalya et al. (2020) to define the time the warning is given to the driver (described in the section Collision warning systems). The second is a driver response model after the FCW is activated. This model includes a) the driver's brake onset timing after the FCW is activated and b) the driver's braking manoeuvre. The brake onset timing is realized as one simple driver reaction time (defined as the time from the warning to when the driver applies the brakes). The driver braking manoeuvre is represented as a piecewise linear function parameterized through maximum deceleration and jerk (see Fig. 2).

The driver reaction time was extracted from a distribution of driver brake reaction times from Sivak et al. (1982) which has been applied in several studies (Haus et al., 2019; Kusano & Gabler, 2012; McLaughlin, Hankey, Dingus, & Klauer, 2009). The distribution was assumed to be log–normal, $X = e^{\mu+\sigma Z}$, with a mean reaction time (μ) of 1.21 s and a standard deviation (σ) of 0.63 s: see Fig. 3. From this distribution, we extracted reaction times that correspond to drivers whose reactions are immediate (without RT), fast (0.57 s), medium (1.07 s) and slow (1.48 s), an adaptation from a previous study (Kusano & Gabler, 2012). As drivers approach the cyclist from behind, they have to decide whether to brake or steer away to avoid a rear-end collision. This decision can be argued to be comparable to the decision to brake in a car-following situation (D. N. Lee, 1976; Yilmaz & Warren, 1995), because the driver is on a rear-end collision course with the cyclist. Thus, the choice of the driver reaction time values, which were adopted from Sivak et al. (1982), was motived by previous research that evaluated the effectiveness of FCW for the car-to-car rear-end scenario (Kusano & Gabler, 2012; McLaughlin et al., 2009). Specifically, Kusano and Gabler (2012) used these values to characterise fast, medium, and slow driver reaction times in response to an FCW that warns the driver at a TTC of 1.7 s.

The driver braking profile was a piecewise linear function (Fig. 2) which assumed that the driver would apply the brakes to reach a level of deceleration, a_c, in response to the warning. This profile has been used in many previous studies that estimate the benefits of FCW and AEB (Bärgman et al., 2017a; Chajmowicz et al., 2019; Kusano & Gabler, 2012; Lubbe and Kullgren, 2015; Sander & Lubbe, 2018). Two different deceleration values (a_c) were used: one is the driver comfort boundary, $a_c = 4$ m/s^2, from Bärgman et al. (2015), and the other is an average of the maximum deceleration from SHRP2 crash data, $a_c = 6.79$ m/s^2 (Bärgman et al., 2017a). Similarly, two values for constant jerk were selected: $j_c = 10$ m/s^3, based on Lubbe and Kullgren (2015), and $j_c = 26.14$ m/s^3, from SHRP2 crash data (Bärgman et al., 2017a). Two driver braking profiles were created from these values, corresponding to comfortable braking (C: $a_c = 4$ m/s^2 and $j_c = 10$ m/s^3) and maximum braking (M: $a_c = 6.79$ m/s^2 and $j_c = 26.14$ m/s^3).

Combining the four reaction times and the two driver braking profiles resulted in eight driver response models (Table 1). The first part of the name for each model reflects the reaction time (without RT, fast, medium, or slow), and the second part reflects the driver braking profile (C or M). As noted, different driver models can greatly affect the outcomes of counterfactual simulations (Bärgman et al., 2017a). Our use of different models, representing responses from immediate and aggressive to slow and comfortable, provides an opportunity to illustrate a range of outcomes. These results can serve as a sensitivity analysis of the FCW, indicating how sensitive it is to different driver responses and helping distinguish between the effect of the FCW system and the effect of the driver response in avoiding collisions.

2.6. Estimating safety benefit

The safety benefit, in terms of number of people suffering injuries of a given severity, was estimated using a dose–response model (Bálint et al., 2013; Korner, 1989; Kullgren, 2008). This model estimates the number of cyclists sustaining an injury of a given severity (fatal, serious, or slight), denoted by E_s, as follows:

$$E_s = \int_0^L f(v) r_s(v) dv \tag{1}$$

where v is the speed of the vehicle at the time of collision measured in kilometres per hour; $f(v)$ is the crash frequency at v (*the number of crashes occurring at collision speed v*); $r_s(v)$ is the risk of sustaining an injury of the given severity level s (fatal, serious, or slight); and L is the largest value v such that $f(v) > 0$ (i.e., the highest collision speed recorded in the events).

When the FCW systems are implemented in the simulations, some crashes are avoided; for those that are not, a decrease in collision speeds may be observed. For the system assessment, the original crash frequency function $f_0(v)$ was replaced by a new crash frequency function $f_w(v)$ with the system implemented. Both functions were calculated from the output of the counterfactual simulations. Estimates corresponding to E_s with and without the systems were computed using the injury risk function $r_s(v)$, constructed for cyclists' fatal, serious, and slight injuries (from the research of Kovaceva, Bálint, Schindler & Schneider (2020)). The function was constructed with an order probit model by applying the inverse standard normal distribution of the probability as a linear combination of the predictor (here, collision speed) on car–to–cyclist crashes from GIDAS data. The order probit model is given as

$$y^* = \mathbf{x}^T\beta + \epsilon$$

Table 2
Coefficients for the injury risk function based on previous work (Kovaceva et al., 2020).

	Coefficient estimate
Vehicle collision speed	0.0319
Intercept slight to serious	1.3679
Intercept serious to fatal	3.5633

Table 3
Number and percentage (in parentheses) of avoided crashes (out of the 73 original crashes) for each system and configuration.

Driver response model	Reference FCW	BB FCW
Without RT-C	23 (31.5%)	59 (80.8%)
Fast-C	5 (6.8%)	46 (63.0%)
Medium-C	0 (0%)	36 (49.3%)
Slow-C	0 (0%)	29 (39.7%)
Without RT-M	67 (91.8%)	67 (91.8%)
Fast-M	36 (49.3%)	62 (84.9%)
Medium-M	4 (5.5%)	52 (71.2%)
Slow-M	0 (0%)	42 (57.5%)

$$y^{*} = s, if \mu_{s-1} < y^{*} \leq \mu_{s} \tag{2}$$

where y^{*} is the injury severity level, x is a vector of predictors, β is a vector of estimated coefficients, ϵ is normally distributed with zero mean and unit variance, s is the injury severity level (i.e., fatal, serious, or slight), and μ_s is the estimated threshold for each level of severity. In this paper, the injury severity is based on police-coded injury severities from GIDAS data.

The injury risk function coefficients estimating the injury severity for the cyclist are provided in Table 2.

Having specified all functions as above, the reduction in number of injuries of severity s was calculated as

$$R_{ws} = \frac{E_{os} - E_{ws}}{E_{os}} \times 100 \tag{3}$$

where E_{os} is the original number of cyclists at injury severity level s, and E_{ws} is the expected number of cyclists at injury severity level s with the system implemented. If the crash was avoided, it was assumed that the cyclist was uninjured.

3. Results

The datasets for this study consisted of 73 crash events distributed among 21 drivers. The average age of drivers was 44 years (standard deviation (SD) = 12 years). The average collision speed was 69 km/h (SD = 13). The average bike speed was 22 km/h (SD = 8). All crash events occurred in daylight and on dry roads. In these crashes (without any FCW system), the estimated numbers of cyclist fatalities, serious injuries, and slight injuries were 8, 49, and 16, respectively.

In each simulation with an FCW applied, either the collision was avoided, or the collision speed was reduced. The number and percentage of avoided crashes for each FCW system and each driver model configuration are shown in Table 3. The BB FCW outperformed the reference FCW at reducing the number of crashes. However, the extent of the safety benefit also depended on the driver model parameters. The configuration *Without RT–M* provided, as expected, the largest safety benefits: that is, the number of avoided crashes was largest when driver response was immediate and braking was maximal for both FCW

Table 4
Estimates of the percentage of injury reduction, R_{ws}, for the two systems and the different driver model configurations compared to baseline events. A negative percentage means an increase in the number of injuries.

	Driver response model	Slight (%)	Serious (%)	Fatal (%)
Reference FCW	Without RT-C	−45.3	47.8	82.4
	Fast-C	−48.5	16.9	54.7
	Medium-C	−24.8	3.9	24.8
	Slow-C	−3.8	0.6	3.8
	Without RT-M	84.1	93.5	96.2
	Fast-M	−11.4	62.7	86.5
	Medium-M	−37.1	12.6	46.0
	Slow-M	−5.8	0.9	6.2
BB FCW	Without RT-C	70.2	82.7	90.0
	Fast-C	35.9	68.8	80.6
	Medium-C	24.9	54.2	67.5
	Slow-C	21.8	43.3	52.9
	Without RT-M	84.1	93.5	96.2
	Fast-M	77.8	86.2	91.1
	Medium-M	51.5	75.8	81.7
	Slow-M	38.7	61.8	68.1

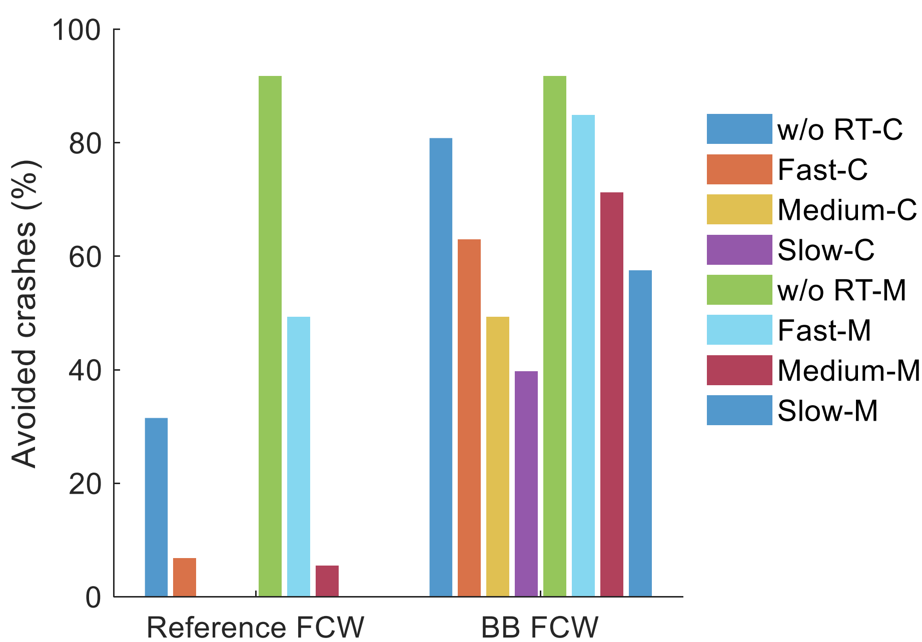

Fig. 4. Percentage of avoided crashes for the two FCW systems and eight driver model configurations.

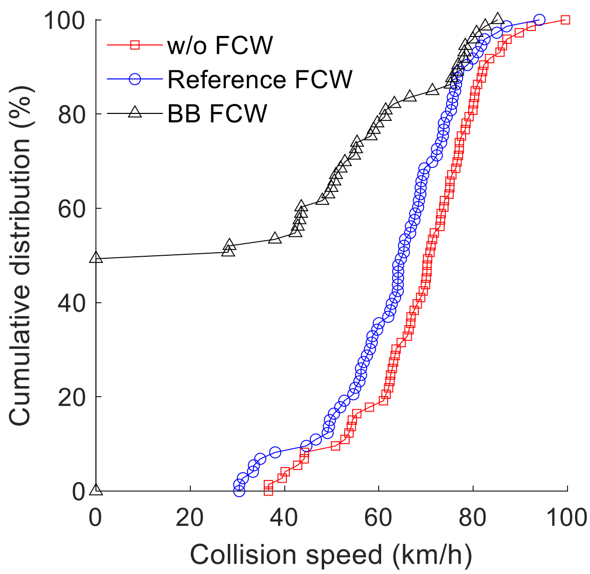

Fig. 5. Cumulative distribution of the collision speeds for different systems with driver model parameters from configuration Medium-C.

systems, which performed equally, avoiding 67 crashes (see also Fig. 4). Unsurprisingly, as the driver's reaction time increased, the safety benefit decreased, and as the driver's maximum deceleration increased, the safety benefit of the system increased, too. These results indicate that more alert drivers (with faster reaction times) and drivers who brake harder (with larger decelerations) are more likely to avoid rear–end collisions.

Table 4 shows the estimated reduction in the percentage of injured cyclists by injury level for both FCW systems. It can be observed that all injury types decreased when the BB FCW was applied. In contrast, for the reference FCW, the proportion of slight injuries (out of all injuries) increased, shown by the negative numbers in Table 4. The numbers indicate a shift towards lower severities; some of the serious and fatal injuries have become slight injuries, since the collision speed was decreased (never increased) with the application of the reference FCW. Although serious and fatal injuries decreased by 1–94% and 4–96%, respectively, these reductions are lower than those of the BB FCW. Overall, with the BB FCW, the reduction in fatalities was 53–96%, in serious injuries 43–94%, and in slight injuries 22–84%. (The percentages reflect the range of results across the different driver response models.)

Fig. 5 compares the collision speed distributions for the baseline (without FCW) and the two FCWs for the configuration *Medium–C*. The BB FCW reduced the number of collisions by 49% and the collision speed for the remaining 37 crashes by, on average, 56.7%, although approximately 27% of the remaining crashes (14% of all crashes) had collision speeds similar to those of the reference FCW. For the reference FCW, all 73 original crashes still occurred, but their collision speeds were reduced (on average by 8.2%). The average collision speeds were 69.4 km/h, 63.7 km/h, and 30.1 km/h, for events without FCW, with reference FCW, and with BB FCW, respectively.

The cumulative distributions of the probabilities for the three injury levels for the different systems are shown in Fig. 6 for the configuration *Medium-C*. The application of the BB FCW decreased the probability of slight, serious, and fatal injuries (but with a shift towards lower severities; see Table 4). The application of the reference FCW decreased the probability of serious and fatal injuries for the remaining crashes. As noted, the decreased probability of fatal and serious injuries resulted in an increased probability of slight injuries (visible in Fig. 6, where the curve 'Reference FCW: slight injuries' is to the right of the curve 'w/o FCW: slight injuries').

4. Discussion

This paper assesses the potential safety benefit of a BB FCW system, with an improved collision threat algorithm integrating driver behaviour model, relative to a reference FCW, using counterfactual simulations of crashes derived from ND data, with the original driver responses removed.

Results show that the BB FCW was able to reduce the severity of most of the collisions in the baseline (original) events. Among the remaining crashes, the BB FCW still reduced the collision speed and concomitant cyclist fatalities and serious and slight injuries with respect to the total number in the baseline events (8, 49, and 16, respectively). Specifically, the reductions in the number of serious injuries (43% to 94%) and slight injuries (22% to 84%) were lower than that of fatalities (53% to 96%); the range of percentages reflects the smallest and largest reductions obtained as a result of different driver response models ('Slow-C' and

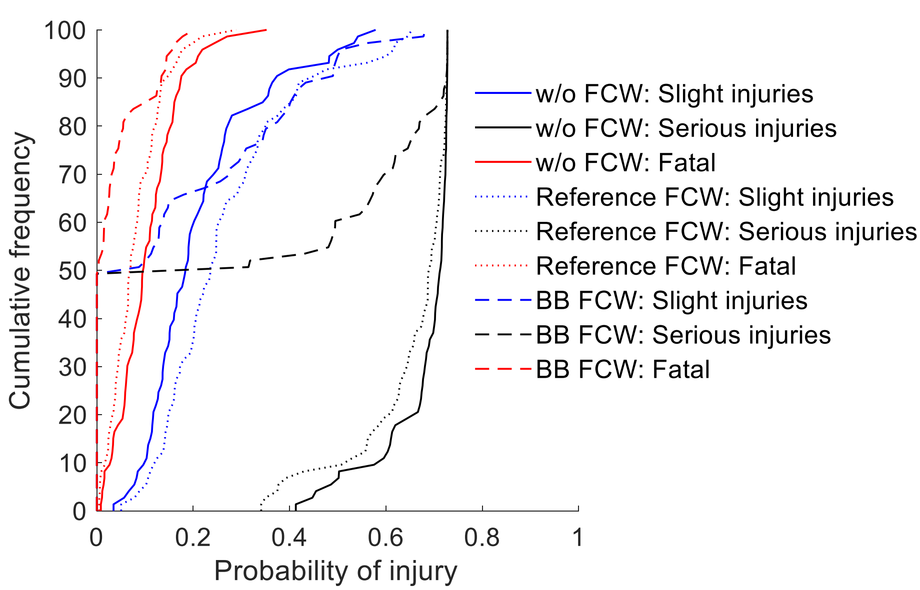

Fig. 6. Cumulative distributions of the probability of injury (fatal, serious, and slight) for different systems with driver model parameters for configuration Medium-C.

'Without RT-M', respectively).

The reduction of injury risk is different for different driver response models used in the simulation. In this study, the driver response model was defined by a reaction time to the warning and a braking profile characterised by a limit on maximum deceleration. Naturally, as the reaction time increased, the safety benefit of the systems decreased—and as the maximum driver deceleration increased, the safety benefit increased. These findings were as expected and follow a trend established in previous studies (Bärgman et al., 2017a; Haus & Gabler, 2019; Kusano & Gabler, 2012). Char et al. (2020) have shown that FCW could reduce or mitigate 84% of car–to–cyclist longitudinal crashes in counterfactual simulations using in-depth crash data from France and Germany. The same authors highlighted that, in this scenario, the drivers' reaction time to the FCW warning was one of the most important factors influencing crash avoidance. Notably, automated emergency braking (AEB) also relies on deceleration values in the braking profile. Chajmowicz et al. (2019) investigated the effectiveness of different AEB sensors and system parameters for avoiding/mitigating frontal car–to–cyclist crashes (using in-depth crash data from France). They showed that the AEB system's maximum deceleration was the most influential parameter at reducing cyclist injuries and fatalities.

Drivers are different in terms of reaction time and braking profile (Ljung Aust et al., 2013; Wu et al., 2017). A fast reaction time may be seen as the braking preparation and initiation time for attentive drivers and drivers that have experienced FCW (Guillen and Gohl, 2019). A slow reaction time may be related to inattentive (e.g., distracted, drowsy, or impaired) driving (Bueno et al., 2014; Harbluk, Noy, Trbovich, & Eizenman, 2007; J. D. Lee et al., 2006). To address driver variability, we used different driver response models that provided a range of typical driver responses within which most responses would fall. This range shows how important the choice of driver response model is. The values we chose could have been replaced by other values, either from the distribution in Fig. 3 (e.g., fast, medium, or slow from the distribution in Sivak et al. (1982)) or from studies that provide a mean reaction time to FCW. For example, we could have used the mean reaction times of 2.1 s and 1.35 s for late and early FCW responses, respectively; these values were reported by Lee et al. (2002), who measured actual reaction times to an FCW. As an additional sensitivity analysis, we conducted simulations with these reaction time values as well, and the conclusions of our study still held. (See Supplementary material for the details.) Since the reported mean reaction times to FCW differ in different studies, one should consider them with care when comparing and using them (Engström, 2011; M. Green, 2000; Markkula et al., 2016). That is, the observed brake reaction time in one scenario under certain experimental conditions may not generalize well to other scenarios (Engström, 2011; Ljung Aust et al., 2013; Markkula et al., 2016). We chose the response time values from Kusano & Gabler (2012), as that study assesses the safety benefit of an FCW similar to the reference FCW used in this paper; further, the work has been cited extensively.

The driver's reaction may also depend on the warning's modality (visual, auditory, or tactile), according to Lylykangas, Surakka, Salminen, Farooq, & Raisamo (2016). They found that tactile and visual-tactile modalities help drivers react faster to the FCW than a visual-only modality. Thus, determining the appropriate warning modality to get the optimal driver reaction to a critical situation should be considered in the design of future ADAS. Depending on the driver's inattention level, FCW may incur decelerations that are too large or too small, thus making the driver uncomfortable or the vehicle unsafe (Fancher, Bareket, & Ervin, 2001; Harbluk et al., 2007; Moon & Yi, 2008). The two levels of deceleration and jerk used in this study represent comfortable braking during normal driving, on one hand, and the average maxima during crashes, on the other (Bärgman et al., 2015, 2017a; Lubbe and Kullgren, 2015).

We observed that when the driver's reaction time was the slowest, FCW alone was not always able to avoid rear–end collisions with cyclists, even with the faster, less comfortable maximum deceleration. (As noted, the two maximum decelerations were 4 m/s^2 and 6.79 m/s^2 (from Bärgman et al. (2015) and Bärgman et al. (2017a), respectively). Furthermore, the sensitivity analysis of possible driver responses (with all three parameters: driver reaction time after FCW and the jerk and maximum deceleration in the brake profile), representing a spectrum of drivers, shows how different driver response behaviours affect the outcome of the FCW within and between the two FCWs.

There are additional ways to improve braking: FCW can also pre-charge the brakes, systems such as brake assist (Dahl, De Campos, Olsson, & Fredriksson, 2019) can help the driver brake harder (and with more jerk), and AEB can further increase safety. It is likely that a combination of these solutions is the best for collision avoidance and injury mitigation (Boda et al., 2018; Cicchino, 2017). However, since AEB increases system deceleration and jerk, having AEB may increase the likelihood that the vehicle is struck from behind, compared to a vehicle that only has FCW (Cicchino, 2017) – potentially resulting in occupant injury (Graci et al., 2019). Further, AEB systems are designed not to intervene until very late, when the crash is imminent. If the road conditions do not allow large decelerations (e.g., due to ice or snow), having the driver decelerate earlier, but at a lower rate, may be beneficial—-which is what FCW supports. The results from the implemented BB FCW suggest that the current 1.7 s TTC threshold from the NCAP protocol is not long enough. If the TTC threshold for the reference FCW were higher than 1.7 s (e.g., 2.1 s), more crashes would probably be avoided. (See Supplementary material for details on the results from an additional sensitivity analysis performed with two more activation thresholds, TTC = 1.3 s and TTC = 2.1 s, for FCW system that is triggering on TTC.) However, there would also likely be more false positives, which the driver would not appreciate. As the threshold for FCW activation increases (e.g., the warning comes while the driver still has a plan to avoid the situation through everyday driving manoeuvres), the probability that the driver does not appreciate the warning increases. In fact, the driver may turn off the system, eliminating its safety benefit entirely. The main reason to use a driver model that includes driver behaviour, including comfort zone boundaries, in the threat assessment FCW algorithm is that the driver is much more likely to accept an earlier warning if the warning is issued after the comfort zone boundary is crossed. By incorporating comfort zone boundaries into its driver model, the BB FCW can issue earlier warnings that are nonetheless outside of the driver's comfort zone (i.e., they would have taken action if they had been attentive to the situation as it unfolded). Using a driver behaviour model in the FCW (realized in this paper as the BB FCW) to enable earlier interventions without nuisance warnings is clearly beneficial.

The estimated safety benefits in this study indicate the substantial potential of FCW for both avoiding crashes and reducing injuries in the car–to–cyclist overtaking scenario. Even when driver braking was limited to comfortable deceleration, half of the collisions were avoided by the BB FCW. This finding may be considered in the design of future systems, which will likely include automated braking in addition to the warning if the drivers do not have the opportunity to avoid the collision by braking within their comfort deceleration.

In this study, a dose–response model was used to estimate the safety benefit across three injury severity levels, as in several previous studies (Bálint et al., 2013; Kullgren, 2008; Kullgren et al., 2019; Lindman et al., 2010). The input parameters of the model are the crash frequency and injury risk functions, which can easily be updated if new data becomes available. It has been shown that safety benefit results may differ when using different injury risk functions (Rosen et al., 2010). For example, the safety benefit results for AEB and steering systems in car–to–cyclist crashes for two injury risk functions were compared. One function was constructed using logistic regression and the other was an order probit model (as used in this work); they showed similar benefits, except that the reduction of fatalities using the former function was somewhat higher (Kovaceva et al., 2020).

The safety benefit results from this study are specific to car-overtaking-cyclist crashes (i.e., not all car–to–cyclist crashes). Yet, they are consistent with the findings by Ohlin et al. (2017), Rosen (2013), and Yue, Abdel-Aty, Wu, & Wang (2018), which demonstrate the great positive impact that ADAS can have on cyclist safety. Furthermore, recently proposed AEB and steering systems for longitudinal car-to-cyclist scenarios reported a 71–90% crash reduction, according to counterfactual simulations (Kovaceva et al., 2020). On the other hand, a retrospective safety benefit assessment using insurance data showed smaller reductions in car–to–car rear–end striking crash rates: 27% for FCW, 43% for low-speed AEB, and 50% for FCW and AEB (Cicchino, 2017), probably due to different sensors in the vehicle. These differences may be explained by Sander (2017), who compared results from prospective counterfactual simulations with those of retrospective analyses. The author suggested that, for AEB that addresses car–to–car rear–end crashes, the prospective assessment may overestimate the benefits by 50%, perhaps due to idealised conditions (sensors or environments) in the simulations. One should therefore consider the results from our study with this possibility in mind. The results will need to be confirmed by retrospective studies. Once sufficient real-world data become available, the effectiveness of the actual system can be evaluated.

4.1. Limitations and future work

In this study, several assumptions have been made on the driver reaction to the warning. First, we assumed that all drivers reacted to the warning to avoid the impending collision. In reality, some drivers simply do not react to it. Second, the counterfactual simulations did not include driver responses other than braking: steering, for instance, would be a reasonable manoeuvre to avoid the collision when no oncoming vehicle is present (Scanlon, Kusano, & Gabler, 2015; Wu et al., 2017). Third, the use of brake reaction times instead of more complex driver response models in simulations which estimate the safety benefit of FCW systems, although ubiquitous (Chajmowicz et al., 2019; Haus et al., 2019; Kusano & Gabler, 2012; McLaughlin et al., 2009; Woodrooffe et al., 2013b), may be overly simplistic. Alternatives which use perceptual cues as input exist, such as accumulation models and threshold models (e.g., Markkula et al. (2016) and Svärd et al. (2020)), but to date these models are rarely used in safety benefit studies found in the literature. Fourth, the driver braking profile assumes that braking increases at a constant rate and remains constant at a specified magnitude. This simplification also has established precedents in previous studies (Brown et al., 2001; Haus et al., 2019; Kusano & Gabler, 2012; McLaughlin et al., 2009; Woodrooffe et al., 2013b). In practice, driver deceleration magnitude can change during braking: Markkula et al. (2016) showed that driver braking is highly dependent on the situation's urgency. Although the accumulation-based models seem to have good validity for car-to-car rear-end situations, it is not obvious that the parameterization available in the literature applies to car-to-cyclist overtaking. Accumulation-based models are even less used for brake control than for brake onset. Since one of our aims was to demonstrate the difference in the magnitude of the benefit of BB FCW for different driver response models (driver reaction time after FCW and the jerk and maximum deceleration in the brake profile), we did not use more complex models of the driver brake response, such as the accumulation model in Svärd et al. (2021; 2020), which is based on event urgency rather than simple reaction times. To keep our model comparison simple, we elected not to include event urgency as a factor. Fifth, friction was not taken into account in this study, because most same-direction car–to–cyclist crashes occur in good weather on dry ground, and friction has not been shown to be a main cause of crashes of this type (Diaz Fernández, Isaksson-Hellman, Jeppsson, Kovaceva, & Lindman, 2020). We assumed dry road conditions. In future implementations, the variability in braking magnitude due to friction and different driver response models (e.g., urgency-based) could be included in the simulations to make them more realistic.

Another limitation is the crash generation process by which the events were derived from everyday driving in UDRIVE. While this is an inherent limitation, the car-overtaking-cyclist scenario on straight roads is a fitting use of ND data, as it is particularly difficult to perform high-quality reconstructions of crashes involving vulnerable road users (Bakker et al., 2017; Barrow et al., 2018; Dekra, 2020; Simms & Wood, 2009). Further, for the car-overtaking-cyclist scenario, the difference between a crash and a non-crash is typically whether the driver brakes or steers away; if the driver fails to perform one of these manoeuvres successfully, the cyclist is impacted in the rear. MacAlister and Zuby (2015) reported that the vehicle did not brake in 94% of all longitudinal car-to-cyclist crashes and in 93% of fatal ones. The failure to brake may be due to lack of attention to the roadway ahead (or failure to see the cyclist). In fact, one of the most frequent factors in vehicle-to-cyclist crashes is driver inattention (Schramm, Rakotonirainy, & Haworth, 2008). A recent systematic review reported that inattention has been frequently listed in study reviews as a cause of these crashes (Prati, Puchades, De Angelis, Fraboni, & Pietrantoni, 2018). Inattention and distraction have been described as two of the ten most frequent causes of vehicle-to-cyclist fatal crashes (ERSO, 2018). Furthermore, the longitudinal-scenario car-to-cyclist crashes were often caused by inattention (Stoll et al., 2016) and often occurred when the driver failed to notice the bicycle (ITARDA, 2018). As long as factors such as the car and bicycle travelling speeds are accurate, simulating crash events by simply removing the driver's behaviour (overtaking) in the original event should provide pre-crash kinematics relatively similar to real-world crashes (and no worse than reconstructions from in-depth crash investigations). Most car-overtaking-cyclist crash scenarios have occurred on straight rural roads with high speed limits and cyclist speeds which did not vary much (Fredriksson et al., 2014; Isaksson-Hellman & Werneke, 2017; Lindman et al., 2015; MacAlister & Zuby, 2015; Op den Camp et al., 2014; Uittenbogaard, Op den Camp, & Montfort, 2016; Wisch et al., 2017). Tests for assessing FCW incorporate these pre-crash characteristics: occurring in rural areas with vehicle speeds of 65–80 km/h and cyclist speeds of 20 km/h (Uittenbogaard, Op den Camp, & van Montfort, 2016). As a result, Euro NCAP started to assess cyclist FCW systems for the same scenario with vehicle speeds of 50–80 km/h and cyclist speeds of 20 km/h (Euro NCAP, 2019). The generation of crashes from naturalistic events is justified, because a) whether an event becomes a crash or not depends only on whether the car driver performs an overtaking or not (e.g., brakes/steers), and b) the pre-crash parameters such as speed and context (e.g., a rural road) are sufficiently similar to real crashes and to the Euro NCAP protocol for ADAS for VRU testing (Euro NCAP, 2019).

Although UDRIVE was a valuable resource for assessing the safety benefit of the BB FCW compared to a reference FCW, the sample size available for the scenario studied here was relatively small. In the future, larger datasets that include a variety of situations (different approaching speeds and road profiles, curvatures, or gradients could be taken into account), assuming that the FCW models can account for these inputs. Furthermore, the safety benefit analyses focused on true positives and neglected false positives. A possible consequence is an overestimation of the safety benefit, as a real system would have to balance the two (Alvarez et al., 2017). The quantification of false positives is a necessary step in optimizing an FCW, in order to maximize real-world effectiveness and minimize negative consequences, but the assessment of false-positive activations was not possible with the data in this study, since only data on true conflicts were available to us. More ND data is needed to validate the models and run more accurate safety benefit analyses, which would need to include an assessment of false positives as well.

This study can serve as a helpful diagnostic step and proof of concept in understanding the potential benefit of the BB FCW. System designers can use our results and further iterate system designs using similar methodologies before the new system is prototyped. Future studies should then aim to estimate the absolute benefit of the system. However, given the difficulties in reconstructing car-to-bicycle crashes (Bakker et al., 2017; Dekra, 2020; Simms & Wood, 2009), it is not obvious that benefit estimates using other, currently available, data sources will be substantially better than the estimates made here for the specific scenario studied here. However, at the very least, complementary studies using data from in-depth crash databases should be run to assess the safety of the BB FCW; those results should be compared with the current study. Further, as with any simulation, all conclusions are only as valid as the data and the underlying models (Stellet et al., 2015). After the simulation step, to develop a production system, prototypes of the system should be tested and validated in a controlled environment (Riedmaier, Ponn, Ludwig, Schick, & Diermeyer, 2020). In addition, counterfactual simulation results can also be combined with real-world test-track results to overcome some of the challenges inherent in methods based on one data type only (Kovaceva et al., 2020). To quantify the real-world safety benefit of the system for a target population or region (e.g., Europe), the results would need to be extrapolated (Chen, Kusano, & Gabler, 2015; Seaman & White, 2013). However, it is not obvious that the baseline events used in this study are representative of the whole of Europe, so extrapolating them would be of dubious benefit. Therefore, the results should only be viewed as relative comparisons, rather than as absolute benefits.

In addition, future studies should use a more specific injury risk function derived from car–to–cyclist overtaking scenarios, rather than the generic function (which includes all crash scenarios between cars and cyclists) used in this study. A more specific function would account for scenario-specific deviations from the average relationship described by the generic function and may include additional predictors, such as cyclist age (Rosén and Sander, 2009) and gender, provided that sufficient data are available for each of the predictors.

In this study, we focused on the safety benefit assessment of FCW, a system that supports the driver in the approaching phase, when there is a risk of a rear–end collision with the cyclist. The system relies on the driver to brake to avoid a collision with the cyclist. However, assuming the system can predict the cyclist's future behaviour from sensor data (e.g., the cyclist increases the distance to the overtaking vehicle), then the system could extend the time horizon for threat assessment and may make it possible to predict the driver's response to the cyclist behaviour and adapt the system activation (e.g., earlier or later activation depending on the cyclist behaviour). The BB FCW should be able to detect the cyclist at a TTC of 6 s, which corresponds to a range of 116 m, while the sensor range to oncoming traffic should be at least 250 m (Rasch & Dozza, 2020). Unfortunately, 250 m is outside the limit of about 150–175 m of the radar sensors that have been on the market for the last two decades (Blanc, Aufrère, Malaterre, Gallice, & Alizon, 2004; Hammarstrand, Fatemi, García-Fernández, & Svensson, 2016; Mukhtar, Xia, & Tang, 2015). However, our analysis does not rely on any unreasonable technological developments, since recent research shows that sensor technology is continuously improving, and a range of 250 m for radar sensors is on the horizon (BOSCH, 2021; Continental, 2021). Furthermore, wireless communication is also a reality; as a result, vehicles could be aware of oncoming vehicles even when visibility is reduced (Belyaev et al., 2013).

The models used in this paper, the driver behaviour model (Rasch & Dozza, 2020) that was integrated into the BB FCW system (Thalya et al., 2020), do not directly address automated driving. It is worth noting, however, that future models may be able to understand situations that autonomous vehicles encounter when deployed in real traffic and may support automated driving by improving the safety of cyclist interactions. The autonomous vehicle can use the information from the models to predict the intent of other road users, so that it acts in a way that neither scares nor injures the cyclist while being comfortable and acceptable for the driver. Furthermore, new collision scenarios arise as the overtaking manoeuvre progresses, such as head-on collisions with oncoming traffic and sideswipes of the cyclist in the passing and returning phases. In these scenarios, new ADAS that also take lateral control (Brännström et al., 2014; Nilsson, Brännström, Fredriksson, & Coelingh, 2016) into consideration may be needed. Assessing the safety benefit of new ADAS that can support the driver during the whole cyclist-overtaking manoeuvre should be explored in future studies. Furthermore, a collision may be unavoidable even with ADAS, due to more critical vehicle kinematics and distances between the road users after the approaching phase, as shown in Dozza et al. (2016). In these cases, a passive safety system may complement the ADAS. Passive systems include pop-up hoods and external airbags to mitigate collisions with the cyclist (Fredriksson, Håland, & Yang, 2001; Fredriksson, Ranjbar, & Rosen, 2015) as well as cyclist-friendly vehicle designs that have low-impact stiffness and large deformation spaces to avoid bottoming out (Hu & Klinich, 2015). Finally, in the future, a method to combine the effects of ADAS and passive safety systems could be investigated to assess the benefits of an integrated system.

5. Conclusion

In this paper, the relative safety benefit of a BB FCW system that supports a driver in the approaching phase of a cyclist-overtaking manoeuvre on rural roads was compared with a reference system. A comparison of this type, using virtual simulations of car-overtaking-cyclist crashes derived from naturalistic driving data, has not been performed before. The simulations included several driver response models, with responses representing different levels of comfort, alertness, or even impairment. Variations in driver responses should be taken into account to optimise the warning timing of future ADAS.

The results of our virtual assessment show that the BB FCW provides, in general, larger safety benefits than the reference system. The BB FCW reduced fatalities by 53–96% and serious injuries by 43–94%, depending on the driver response model (reaction time and brake profile). Even with a slow driver reaction time and a braking profile with low jerk and comfortable deceleration, the BB FCW managed to reduce the crashes by 49%. However, this result shows that FCW alone may not be sufficient to avoid all rear–end collisions with cyclists; an autonomous emergency braking system may be a complementary solution.

In this study, the safety benefit from FCW might be overestimated, due to the focus on the true positives. More real-world data, including crashes, is needed to validate the models and verify the estimated safety benefit. Nevertheless, the comparison with the reference FCW, based on Euro NCAP, clearly shows the potential improvements in safety benefit when a driver behaviour model is integrated in the collision threat algorithm of the BB FCW. Future work should focus on extending the virtual safety assessment to new ADAS (accounting for both lateral and longitudinal control) to support the driver in all phases of the overtaking manoeuvre.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aap.2021.106513.

Appendix

Data description

Overtaking events (N = 73) in which a car driver overtakes a single bicyclist on a straight rural road were extracted from the UDRIVE naturalistic driving (ND) data. In this study, data were extracted only for rural roads (excluding highways) that have two lanes: one in each direction. The lane width was 3.2 m (SD = 0.3). For the extracted (normal driving) events, the average vehicle speed was 65 km/h (SD = 14). The average oncoming vehicle speed was 68 km/h (SD = 16). The average cyclist's speed was 22 km/h (SD = 8). The width of the cyclist was calculated as the average value of the cyclist's width as detected by the smart camera, 0.65 m.

A smart camera recorded the cyclist's distances (lateral and longitudinal) from the vehicle, and the vehicle's distances to the lane edges (adjacent lane and road shoulder). The camera provided relative speed between the ego vehicle and the cyclist, which was used to derive the cyclist speed. Because the lateral position of the cyclist was relatively variable and the cyclist was not always visible to the smart camera, the cyclist's trajectory during the overtaking manoeuvre was approximated with a straight line. The slope of the line, corresponding to the cyclist heading angle, was approximated to follow the road edge (this was a valid approximation, since the analyses were performed on overtaking manoeuvres on a straight road and the cyclist position was manually verified from video observations).

Behaviour-based FCW model flow chart

The flow chart of the behaviour-based FCW is shown in Fig. 7. This logic is followed for each time-step in the simulation. The car and bicycle were considered to be on a collision course if their future positions, assuming constant speeds and heading, overlap as the car approaches the bicycle to perform the overtaking manoeuvre. That is, if the vehicles' positions overlapped at any point in the predicted trajectory, a collision was predicted, and the next step was to take into account the driver behaviour model prediction and the driver current state (the algorithm flow as outlined above). The BB FCW triggered a warning to the driver when there was a mismatch between the behaviour model prediction and the current driver state (i.e., braking and steering measured from the vehicle network).

In the simulations, in each time step, BB FCW predicts if the vehicle

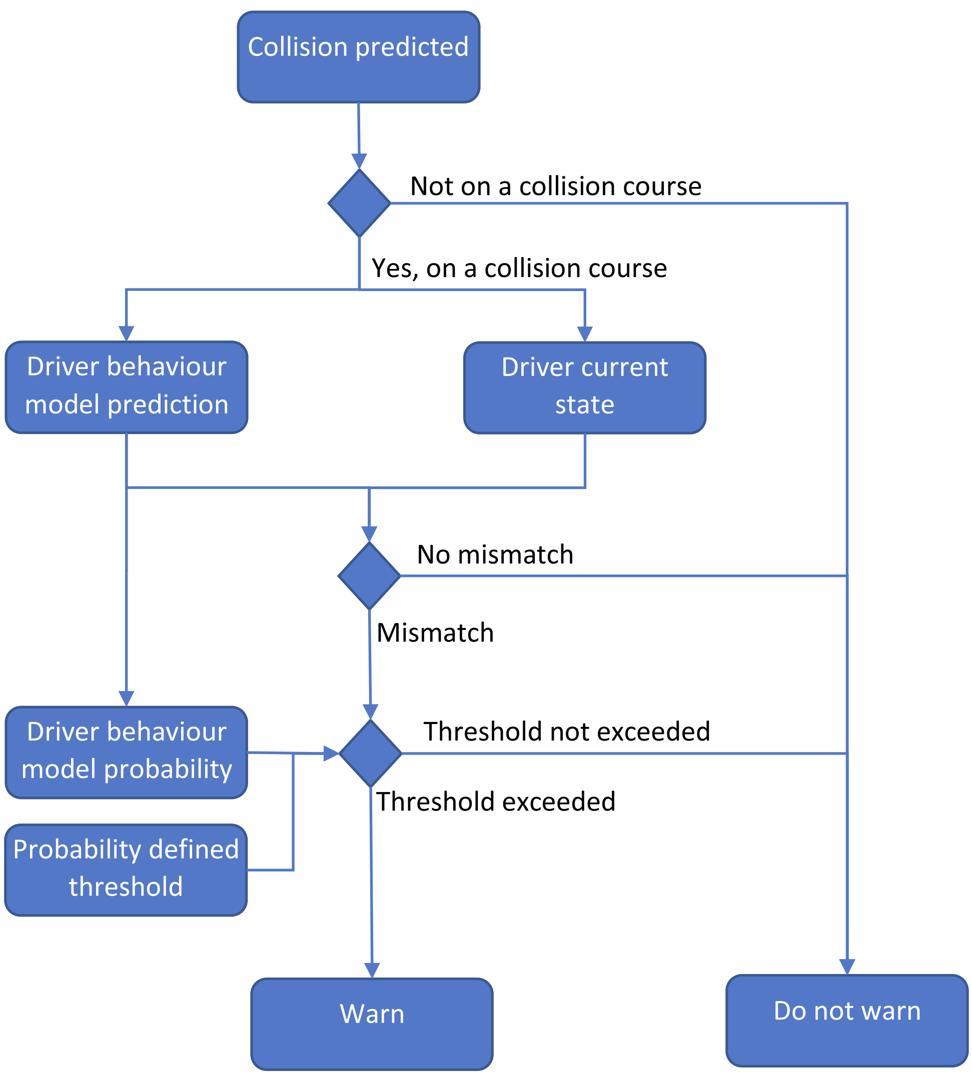

Fig. 7. Flow chart of the BB FCW model.
Adapted from Thalya et al. (2020)

and the cyclist are on a collision course for a specific prediction horizon. The system continuously monitors the situation, such as the driver's actions (applying the brakes, or steering away from the cyclist) and whether the cyclist is moving away from the future vehicle's trajectory. If the situation is not risky and there is no mismatch between the current and predicted driver's action, the BB FCW will not warn the driver. Since the simulated events are crashes, the vehicle and the cyclist are on a collision course, and eventually BB FCW issues a warning.

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