D2.5 DESCRIPTION METRICS FOR TRAFFIC INTERACTIONS

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Executive summary

The SAFE-UP project aims to proactively address the novel safety challenges of the future mobility systems through the development of tools and innovative safety methods that lead to improvements in road transport safety.

Future mobility systems will rely on partially and fully automated vehicles to reduce traffic collisions and casualties by removing causal factors like driver distraction, fatigue or infractions and by reacting autonomously to emergency situations. On the other hand, they may introduce new collision risk factors or risky behaviours when interacting with other traffic participants.

SAFE-UP's Work Package 2 will further the understanding of the impact of vehicle automation technologies on safety by leveraging newly developed behavioural traffic simulation tools. These tools will allow one to simulate specific road networks with a variable proportion of automated vehicles to non-automated traffic participants (including human-drivers, pedestrians, cyclists, and powered two-wheelers). The simulation models will be detailed enough to realistically recreate the effects of unexpected events (like surprise cut-ins). In this way, one will be able to determine whether these technologies induce changes (positive or negative) in surrogate indicators of traffic safety.

An important surrogate indicator of safety is the occurrence of safety-critical interactions in different driving scenarios. The analysis of interaction criticality is the main focus of the partners in Task 2.2, who authored this report. This report[1] summarizes the state of the art on reasoning about criticality (or severity) of driving interactions and:

- Recommends the best suited metrics to recognize safety-critical and non-safety critical driving interactions in simulation (Section 2);
- Identifies areas where the literature may be lacking and describes the initial research and development plans for each of the partners of Task 2.2 (Section 3).

An important conclusion of this survey is that the criticality of a driving interaction depends on the type of traffic participants involved. For instance, a critical interaction between a car and a motorcycle may not be critical between two cars. Also, an interaction between a car and a pedestrian may not be critical from the vehicle's perspective, but perceived as critical from the pedestrian's perspective. Consequently, the information is presented from three different perspectives: motor vehicles, vulnerable road users, and powered two-wheelers.

Finally, a selection of the main criticality metrics to be used to analyse simulation results is presented in the Conclusion & Recommendation section (Section 4).

[1] This report is our contribution to this topic. A final report, D2.14, will be published in July 2022.

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List of abbreviations

Abbreviation	Meaning
CI	Crash Index
CIF	Criticality Index Function
CPI	Crash Potential Index
CPM	Crash Propensity Metric
D	Deliverable
DRAC	Deceleration Rate to Avoid Crash
DSS	Difference of Space distance and Stopping distance
H	Headway
KRI	Key Risk Indicator
MADR	Maximum Available Deceleration Rate
ML	Machine Learning
MTTC	Modified Time-to-Collision
NDD	Naturalistic driving data
PET	Post-Encroachment Time
PICUD	Potential Index for Collision with Urgent Deceleration
PSD	Proportion of Stopping Distance
PTW	Powered Two-Wheelers
RBR	Required Braking Rate
SMoS	Surrogate Measures of Safety
SotA	State-of-the-Art
T	Task
TET	Time Exposed Time-to-Collision
TIDSS	Time Integrated DSS
TIT	Time Integrated Time-to-Collision
TTA	Time-to-Accident
TTC	Time-To-Collision
TTCD	Time-to-Collision with Disturbance
UD	Unsafe Density
VRU	Vulnerable road user
WP	Work Package
SV	Stimulus Vehicle
RV	Response Vehicle

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1. Introduction

1.1 The EU Project SAFE-UP

The SAFE-UP project aims to proactively address the novel safety challenges of the future road mobility environment by developing tools and innovative safety methods, leading to improvements in road transport safety.

Future mobility systems are expected to make use of vehicles with full or partial automation of the driving task, the so-called SAE L3/4/5 vehicles (SAE, 2018). By supporting (or even replacing human) drivers during the driving task, such vehicles may help improve road safety by removing some of the known sources of collisions (e.g., driver distraction) or by taking control during critical situations (e.g. automated emergency braking). On the other hand, automated vehicles may introduce new collision risk factors (e.g., increased distraction during transition of control) or induce new risky behaviours in other traffic participants (Hamilton, 2019).

The true impact of vehicle automation technologies on road safety will become apparent in the decades to come, as it depends on social and market trends that are difficult to forecast (like technological developments in sensors for automated vehicles, market penetration and acceptance of automation technologies, etc.).

Through the work in Work Package (WP) 2, SAFE-UP will further the understanding of the future impact of vehicle automation technologies by leveraging newly developed behavioural traffic simulation tools. These tools, currently under development by SAFE-UP's partners in Tasks (T) 2.3 and 2.4 (see Deliverable (D) 2.4 for details), will allow one to simulate specific road networks with a variable proportion of vehicles equipped with automation technologies. By analysing the simulation results, one will be able to determine whether these technologies induce changes (positive or negative) in surrogate indicators of traffic safety.

An important surrogate indicator of safety is the occurrence of safety-critical interactions in different driving scenarios. Safety-critical (and non-safety-critical) interactions are generally defined by applying thresholds to particular criticality metrics. The identification and/or development of criticality metrics for driving interactions is one of main goals of T2.2. Such metrics can be used to develop collision avoidance algorithms, to test the capabilities of specific vehicle automation technologies or, as in the case of T2.5, to identify safety critical interactions in micro-simulations. Thus, the metrics presented in the rest of this document play an important role in the contributions of this project.

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1.2 Objective of this Report

This report presents a summary of the state of the art on reasoning about criticality (or severity) of driving interactions. The aim is twofold:

- To survey the literature of severity metrics in order to identify those that can be used to recognize safety-critical and non-safety critical driving interactions.
- To identify areas where the literature may be lacking and describe the initial research and development plans for each of the partners of T2.2.

It is important to remark this report constitutes the initial version of WP2's contribution to this topic. A second and final version of this report, D2.14 (expected in June 2022), will include the work products of the partners of T2.2, and a more detailed connection to the scenarios and use cases defined in D2.6 (expected in September 2021).

1.3 Report Organization

The rest of the report is organized as follows: Section 2 presents an overview of the available literature on severity metrics for driving interactions. To this end, we provide first a brief glossary of common terms used in the document (Section 2.1) and a well-established approach to relate traffic interactions and safety (Section 2.2). The literature overview is presented in Sections 2.3-2.5 from three different perspectives: motor vehicles, powered two-wheelers (PTWs), and vulnerable road users (VRUs), respectively (the order reflects the decreasing level availability of literature on these topics). Next, in Section 0, we present a summary of the T2.2 partners' initial research and development plans, which is followed by our conclusions and recommendation in Section 4.

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2. Traffic Interactions and Safety

This section summarizes the literature on severity metrics for driving interactions. As mentioned in Section 1, the metrics are presented from three different perspectives (motor vehicles, PTWs and VRUs) and will be used to identify safety-critical (and non-safety critical) driving interactions in traffic (micro) simulations.

These three perspectives are needed because the criticality of a driving interaction depends on the type of traffic participants involved. For instance, an interaction deemed critical between a car and a motorcycle may not be critical between two cars. Further, an interaction between a car and a pedestrian may not be critical from the vehicle's perspective, but perceived as critical from the pedestrian's perspective.

It is important to remark that there is significantly more literature available on assigning criticality to interactions from the motor vehicle perspective than from the PTW or from VRU perspectives (the latter is the least represented perspective in the literature).

Sections 2.1 and 2.2 next introduce common terminology that aid in the description of the metrics presented in Sections 2.3-2.5.

2.1 Basic Terminology

The terms and definitions presented here are the result of the work of a task force formed by SAFE-UP partners from different work packages charged with defining a common terminology for the project. A complete glossary will be published elsewhere. However, main terms relevant for Task 2.2 as presented next.

2.1.1 Microscopic traffic simulation

A microscopic traffic simulation is a form of agent-based simulation wherein "…traffic flow is based on the description of the motion of each individual vehicle composing the traffic stream" (Barceló, 2010).

In such simulations, a section of (a possibly real) road network is first constructed, including infrastructural elements like lanes, roundabouts, lane marking, traffic lights and signals, etc. The network is then populated by individual traffic participants (motor vehicles, VRUs, etc.), whose behaviour is prescribed by models (e.g., car following (Alexiadis, Jeannotte, & Chandra, 2004)). The individual participant then traverses the network and interacts with each other following their own individual behaviours. The models are generally calibrated in such a way that metrics such as traffic flow and density reach measured levels in the real world.

While traversing the network, different participants will interact with each other under different scenarios. These are defined next.

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2.1.2 Scenario and scenes

A scenario describes the traffic, infrastructure and environment (including e.g. weather and lighting conditions) for the simulation and consists of a sequence of scenes. It is limited in terms of time and space (ISO 21934, 20XX).

A scenario can be considered to be a sequence of scenes. A scene describes a snapshot that encompasses the mobile and immobile elements of the traffic, infrastructure and environment, and the relations between these elements.

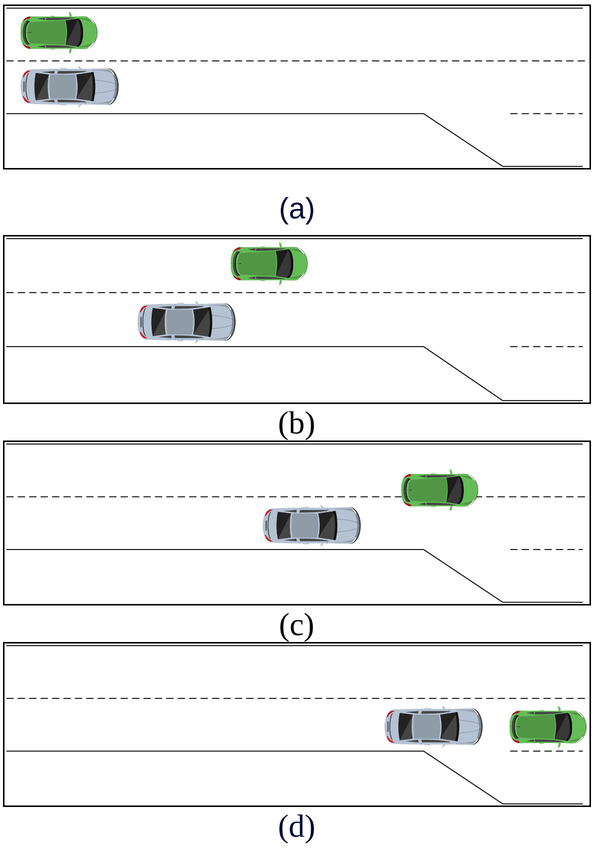

Figure 1: Scenario example (overtake manoeuvre). It is composed of 4 scenes (a)-(d).

The scenarios give rise to interactions among traffic participants. When one or more interactions are safety-critical (e.g., if a severe intervention is needed to avoid a collision) the scenario is considered to be a safety-critical scenario.

2.1.3 Interactions

As mentioned, scenarios give rise to interactions. By interactions we mean situations where the behaviour of at least two traffic participants can be interpreted as being influenced by a

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space-sharing conflict, that is, by their intention of occupying the same region of space at the same time in the near future (Markkula, et al., 2020).

Interactions in which only the behaviour of one traffic participant is influenced by the space-sharing conflict can be considered to be reactions.

2.1.4 Surrogate measures of safety

Traffic interactions are very frequent but traffic accidents are very rare. Although not all traffic interactions lead to accidents, some interactions are more severe than others and some lead to collisions.

The underlying hypothesis is that crashes result from a temporal sequence of events in which a conflict event occurs prior to a crash event (Laureshyn, et al., 2016). Since conflicts and collisions are aligned on the same continuum of events, the frequency of the low-severity events (conflicts) can be used to predict that of high-severity events (collision).

Surrogate Measures of Safety (SMoS) are metrics that quantify the severity of a traffic interaction. As they help characterise the initial conditions and frequency of conflicts, they act as “surrogates” for the likelihood of collision events.

2.2 Driving Interaction and Severity

For the purpose of identifying future safety-critical scenarios, it is necessary to be able to reason about the level of criticality, i.e., severity, of the interactions that occur in such scenarios. A useful approach to relate driving interactions and severity is shown in Figure 2. It was first introduced by (Svensson & Hydén, 2006).

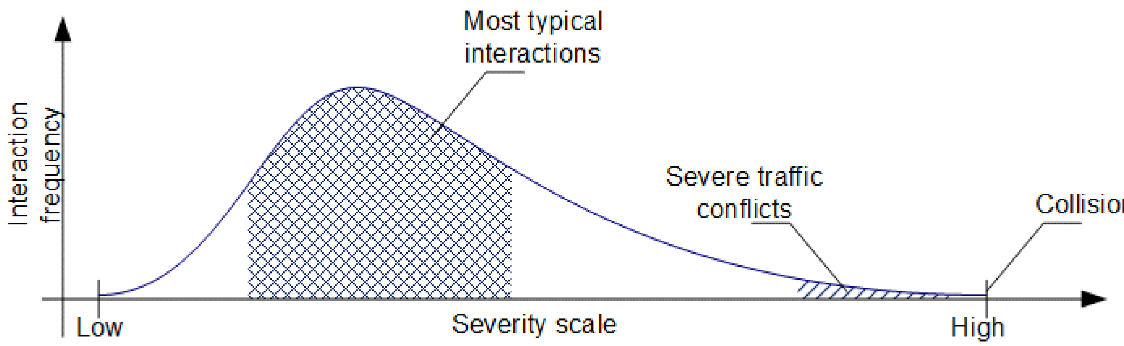

Figure 2 Driving interaction frequency distribution as a function of their severity. Adapted from (Svensson & Hydén, 2006)

This figure shows the frequency distribution (i.e., the histogram or probability density function) of driving interactions according to their severity. The authors did not specify how severity is defined, but remarked that the driving interactions with highest severities are those that become collisions. These are also very rare. Given their rarity, these types of

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interactions cannot serve as the basis to define critical scenarios. Instead (Svensson & Hydén, 2006) suggested to use the so-called severe traffic conflicts. These are interactions that become collisions if none of the traffic participants involved takes an (emergency) action. Severe traffic conflicts are generally defined by defining thresholds over measures of intervehicle separation (based on space, time or speed). As they are more abundant in available driving data, they have served as the basis for defining safety-critical scenarios in the past few decades (see references in Sections 2.3-2.5). Finally, non-safety-critical interactions are rarely defined in the literature. However, they could be defined as those interactions that are not severe traffic conflicts.

It is important to remark that the precise distribution of interactions as functions of severity changes with the scenarios, the location, the type of traffic participants, etc. It should be customized based on specific driving data (see, e.g., (Tejada, Manders, Snijders, Paardekooper, & de Hair-Buijssen, 2020). It also changes with the specific definition of severity one uses. Nevertheless, this approach provides a useful way to relate the research and development efforts by the partners in T2.2., as explained in Section 0.

2.3 Motor Vehicle Perspective

From the perspective of car-car interactions, two participants are normally defined. The ego or response vehicle (RV), which is the vehicle under study, while the other vehicle is called the stimulus vehicle (SV). The RV responds to a certain stimulus triggered by the SV. The trigger can be driving close, decelerating, changing lanes, driving in a path of potential conflict (for example at junctions). This trigger causes the response vehicle to respond in a certain way in order to lower the risk of collision (Cunto F. , 2008). The potential risk is thus measured for the ego (response) vehicle.

For example, when the interaction is between a follower and a leader, the follower is the response vehicle while the leader is the stimulus vehicle. In a cut-in scenario, the stimulus vehicle is the vehicle doing the cut-ins while the response vehicle responding directly to the cut-in. In a crossing scenario at a junction, the stimulus vehicle is any vehicle in a path of potential conflict with the ego vehicle.

Although this description focuses on car-car interactions, in general, the vehicle perspective should consider interactions between a car and another object like pedestrian, cyclist, powered two-wheelers. Indeed, the interactions with the various objects may share similar characteristics described above (leader, follower, response and stimulus), however, there are clear differences in the perception of risk. These differences arise due to differences in dynamics (speeds, acceleration, braking capabilities), physical properties of the object (size, shape, strength) and even human behaviour (drivers tend to behave differently when following another car compared to when following a cyclist).

In theory, most of the risk metrics defined for car to car-car interactions can be adapted for use in a car to object situation. In most cases, the formula for the metrics will remain the same but the threshold for considering severity will be different for different objects. This

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should be taken into account when using the suggested metrics. In the future, it is expected that appropriate thresholds for various car-to-object interactions will be derived from literature and added to this report to give a complete coverage of all types of interactions.

2.3.1 SMoS for Car-Car Interactions

Traditionally, traffic safety studies for car-car interactions relied on the records of reported vehicle crashes, field operational test data and naturalistic driving data (NDD), etc. Such studies have been effective to identify the factors influencing traffic safety (Dingus, et al., 2016; Mullakkal-Babu, Wang, He, Arem, & Happee, 2020) and to draw realistic conclusions on the effectiveness of automotive applications such as Automated Emergency Braking and Forward Collision Warning (Yue, Abdel-Aty, Wu, & Wang, 2018). However, the dependency on recorded data is a major limitation of this approach, as crashes or safety-critical cases are rare events and the recordings may not contain all information required for analysis. Moreover, this method cannot be applied to measure severity for future interaction scenarios that are yet to appear in the traffic. An alternative approach to severity assessment, that does not rely on crash records, is by certain metrics estimated from simulations. In this approach, the traffic of the target road facility is simulated at high resolution and the simulations are post-processed to estimate the magnitude and frequency of one or more severity-metrics. The distributions of these metrics are then statistically analysed to draw conclusions about the interaction classifications. There exist several statistical methods for such analysis, for example alternate hypothesis tests (Bagdadi, 2013; Morando, Tian, Truong, & Vu, 2018), curve fitting (St-Aubin, Miranda-Moreno, & Saunier, 2013), probabilistic causal models (Davis, Hourdos, Xiong, & Chatterjee, 2011; Kuang, Qu, & Wang, 2015) and extreme value theory (Songchitruksa & Tarko, 2006). Currently, simulation-based severity metrics have been used to predict the traffic-safety impacts of automotive applications related to Intelligent Transportation Systems (Liu, Wei, Zuo, Li, & Yang, 2017; Jeon & Oh, 2017; Dedes, et al., 2011). Consequently, the applied severity metrics have a huge impact on identifying car-car interactions.

The car-car interaction severity can be quantified by various metrics that are estimated from the simulated vehicle trajectories. The variation of these metrics is analysed to interpret and explain the collective traffic safety within the studied road stretch. As mention in Section 2.1.4, such measures are known as SMoS (Gettman & Head, 2003; Laureshyn, et al., 2016), and a prominent example is Time-To-Collision (TTC). These metrics indicate a potential conflict between two road users. The underlying hypothesis is that a crash process is a temporal sequence of interactions in which a conflict interaction (safety-critical situation) occurs prior to a crash interaction (vehicle accident) (Laureshyn, et al., 2016). Defining the crash process this way provides theoretical credibility for traffic interaction classifications. Since conflicts and crashes are aligned on the same continuum of interactions, the frequency of low-risk interactions (conflicts) can be used to predict the frequency of high-risk interactions (crashes) (Laureshyn, et al., 2016).

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2.3.2 Classification of SMoS

The literature on SMoS is rich and diverse and can be broadly divided into two categories. The metrics in the first category are based on spatial and temporal proximity to the collision. Examples of this include Post Encroachment Time (Zheng, Ismail, & Meng, 2014), TTC and its derivatives, Potential Index for Collision with Urgent Deceleration (Bevran & Chung, 2012), Deceleration Required to Avoid a Collision (Archer, 2005), Safety Field Strength (Wang, Wu, Zheng, Ni, & Li, 2016). The second category includes metrics based on driver actions such as maximum braking, jerk rate (Bagdad & Várhelyi, 2011), standard deviation of lateral position (Niezgoda, Kamiński, & Kruszewski, 2012) and acceleration noise.

In this report, SMoS are classified into three categories according to (Shi et al,2018) defined below:

- **Behaviour**: These are metrics calculated based on current behaviour with no evasive action taken into account (e.g. braking). These are mostly **time-based**
- **Avoidance**: These are metrics calculated based on current behaviour and current evasive action. These are usually **evasive action-based**
- **Margin Indicators:** These metrics are calculated based on the final outcome of an evasive action. These are used to check whether there is enough space to complete evasive actions. These are usually **distance-based**.

In addition to the classifications above, risk metrics are also classified based on how they are calculated in time. Two categories are defined:

- **Instantaneous:** which are calculated at specific time instant
- **Aggregated:** which are calculated over a specific time-period.

Finally, the risk metrics can also be classified according to the difficulty in the calculation. The difficulty is related to how easy the parameters needed for the metrics can be obtained, how quickly it is to make the calculations and finally if the metric is easy to understand. Three categories are defined:

- **Simple**: Easy to interpret, easy to calculate and parameters needed are easy to obtain.
- **Moderate**: Easy to interpret, parameters are easy to obtain but the calculation takes time.
- **Difficult**: Metric is not very easy to interpret, parameters difficult to obtain and calculation takes time.

The described classifications for some selected severity metrics is summarised in Table 1. For each metric, variables like speeds , positions and length are required for both the subject vehicle and the response vehicle. Since these metrics are made to be used for simulation, positions are preferred to distance as distance can be easily derived from positions. In the simulation environment, positions of vehicles are defined with respect to a reference point

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in the vehicle(front, back or centre) and the network properties like beginning of a link or a specified coordinate system. This information is sufficient to calculate any type of inter-vehicle distances like front to front, front to back depending on the definition and formula of the metric. A more extensive list of severity metrics including the exact formulas used to them is presented in Table 5 in the appendix.

Table 1: Classification of severity metrics

Metric	Unit	Definition	Variables needed	Calculation difficulty	How metric is calculated	Type of metric
Time to Collison (TTC)	(s)	The time until a collision between the vehicles would occur if they continued on their present course at their present speeds.	• Speeds • Positions • Vehicle Length	Simple	Instantaneous value	behaviour (time-based)
Time Exposed Time to Collision (TET)	(s)	The total time a vehicle TTC is lower than given threshold in a given time period	• TTC Time Series • TTC threshold • Total Time Period • Number of discrete time intervals in Time Period	Moderate	Aggregated Single value within a time Period	behaviour (time-based)
Time Integrated Time to collision (TIT)	(s)	Integral of the TTC-profile during the time it is below the threshold	• TTC Curve • TTC threshold • Total Time Period • Number of discrete time intervals in Time Period	Difficult	Aggregated single value within a time Period	behaviour (time-based)
Modified Time to Collision (MTTC)	(s)	Modified models which considers all of the potential longitudinal conflict scenarios due to acceleration	• Speeds • Positions • Accelerations • Vehicle Length	Moderate	Instantaneous value	behaviour (time-based)

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		or deceleration discrepancies				
Post Encroachment Time (PET)	(s)	The time between the moment that a road user (vehicle) leaves the area of potential collision and the other road user arrives collision area.	• Time of detection of first vehicle Speed of first vehicle • Length of first vehicle • Distance between first and second vehicle • Speed of second vehicle • Length of second vehicle • Path of first vehicle • Path of second vehicle	Difficult	Instantaneous value	behaviour (time-based)
Deceleration Rate to Avoid Collision (DRAC)	m/s²	Differential speed between a following/ response vehicle and its corresponding subject/ lead vehicle (SV) divided by their closing time.	• Speeds • Positions • Vehicle Length	Simple	Instantaneous Value	Avoidance (evasive-action based)
Crash Potential Index (CPI)		Probability that a given vehicle DRAC exceeds its maximum available deceleration rate (MADR) during a given time interval.	• MADR pdf distribution over different road and weather conditions DRAC	Moderate	Aggregated value over a time interval	Avoidance (evasive-action based)

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		Driver reaction time can be incorporated in DRAC modified CPI				
Time to Accident (TTA)	(s)	Time-to-Accident (TTA) is the time that remains to an accident from the moment that one of the road users starts an evasive action if they had continued with unchanged speed and directions	• TTC • Braking detection using speeds and acceleration Can also be calculated empirically using Swedish formula TA formula	Moderate	Instantaneous Value	Avoidance (evasive-action based)
Proportion of stopping distance (PSD)		Ratio between the remaining distance to the potential point of collision and the minimum acceptable stopping distance.	• Acceptable maximum deceleration Point of potential accident	moderate	Instantaneous Value	Margin (distance-based)
Potential index for collision with urgent deceleration (PICUD)	(m)	Distance between the two vehicles considered when they completely stop.	• Initial distance • Deceleration rate • Reaction time	moderate	Instantaneous Value	Margin (distance-based)

2.3.3 Recommended SMoS for car-car accident prediction

The availability of several surrogate safety measures makes it difficult to select which metrics to use for identifying potential car-car accidents in urban, rural and highway scenarios.

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There are currently many ongoing research efforts to establish the relationship between these metrics and actual accidents.

In one of such studies carried out to measure the effectiveness of severity metrics to predict accidents, an experimental procedure was performed in using video data of actual accidents on a highway in Singapore (Shi, Wong, Li, & Chai, 2018). The goal was to identify whether some metrics can be used to distinguish accidents from non-accidents using different threshold values. Such indicators are called key severity indicators.

The following are the main findings from the study (Shi, Wong, Li, & Chai, 2018):

1. The performance of each SMoS is different in measuring severity. **TIT** and **CPI** are better in identifying potential accident conditions from normal interactions.
2. **TIT** can be used to identify many severe traffic conflicts while **CPI** is helpful in further identifying the severest conditions (the near-accident) from among these severe conditions.
3. For each SMoS, various threshold values are required to classify the level of severity.
4. **PSD** is helpful to describe the spatial proximity in emergency situations (for example during an emergency brake).

Based on these conclusions, the following classification of severity is recommended for highway scenario (Shi, Wong, Li, & Chai, 2018):

- **LOW RISK**: If **CPI**=0 and **TIT**=0 and **PSD**≤ 1
- **MEDIUM RISK**: **CPI**=0 and **TIT**> 0
- **HIGH RISK: CPI**> 0

For urban scenarios, a study was performed at various in intersections in the United States (Gettman, L, T, Shelby, & S., 2008). A surrogate safety assessment model (SSAM) was developed and used for this purpose. For the classification of potential conflicts at intersections, **TTC<1.5** and **PET<5.0** are recommended (Gettman, L, T, Shelby, & S., 2008).

For rural scenarios, no specific studies were found to give recommendations for SMoS. However, most recommendations for the urban and highway scenarios could be used for rural ones, depending on speed and infrastructure. For rural roads with high speeds and no intersections the recommendations for highway could be used, while for rural areas with low speeds and intersections, the recommendations for urban scenarios would apply.

In order to use the above recommended classification of severity, threshold values for several other SMoS like **TTC**, **DRAC** are required. For example **TTC** threshold values are used to calculate **TIT** while **DRAC**, **MADR** threshold values are used for calculating **CPI**. Table 2 below shows recommended threshold values, the sources they are derived from and which scenarios the metrics are suited for. A more complete description of severity metrics and appropriate thresholds for various scenarios is presented in the appendix.

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Table 2: Threshold values for recommended car-car SMoS (Shi, Wong, Li, & Chai, 2018)

Metric	Threshold	Source	Scenario
TTC	1.5-4.0 s	(Van der Horst, 1990)	Highway, Urban, Rural
DRAC	3.3-3.4m/s^2	(Archer, 2005), (Guido, Saccomanno, Vitale, Astarita, & and Festa, 2011)	Highway, Urban
MADR **For pavement surface conditions**	Average (m/s^2) 8.45 Standard deviation (m/s^2) 1.40 Truncated Normal Distribution Upper limit (m/s^2) 12.68 Lower limit (m/s^2) 4.23	(Cunto & Saccomanno, 2008), (Guido, Saccomanno, Vitale, Astarita, & and Festa, 2011)	Highway, Urban
CPI	>0	(Guido, Saccomanno, Vitale, Astarita, & and Festa, 2011)	Highway, Urban
PSD	<1	(Guido, Saccomanno, Vitale, Astarita, & and Festa, 2011)	Highway
PICUD	0	(Shi, Wong, Li, & Chai, 2018)	Highway, Urban
Reaction Time	1.0(s)	(Uno, Iida, & Yasuhara, 2003)	Highway, Urban, Rural
TTA	Generally, 1.5s is used to distinguish serious conflicts and it worked well for urban roads with low speeds. For rural roads with high speeds<1.5s is recommended	(Mahmud, Md, Hoque, & Tavassoli., 2017)	Rural, Urban
PET	Values between 1.0 to 1.5s are considered critical However, some studies have found values between 5 and 6.5s to match well with aggregate crash data The SSAM uses 5.0s as default threshold value	(Mahmud, Md, Hoque, & Tavassoli., 2017) (Gettman, L, T, Shelby, & S., 2008)	Urban

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2.4 PTW Perspective

As in the case of car-to-car interactions, previous research has analysed interactions between PTWs and cars with crash data, analysing the main factors contributing to crashes (Van Elslande, 2002; Huertas-Leyva, Baldanzini, Savino, & Pierini, 2021) and developing models to predict injury severity (Savolainen & Mannering, 2007). However, collision cases represent only a specific risk scenario that, due to different factors, ends in a collision. Therefore, new studies with traffic models that include PTWs are needed to measure the risk of different interactions and to better understand the patterns of both safe and high-risk interactions in order to quantify risk.

Current traffic models are predominantly composed of passenger cars and usually do not take into account the characteristics of motorcycle/mopeds behaviour (i.e. PTWs). Modelling riding patterns of PTWs through road traffic is indeed challenging because of its complexity in detailing the chaotic and erratic trajectories of PTWs (Das & Maurya, 2018). Previous simplification of models of PTW riders' behaviour have focused on mixed traffic models that apply the models of car drivers' behaviour to motorcycles that are suboptimal because of the previously exposed reasons (Ksontini, Espié, Guessoum, & Mandiau, 2012; Lin, Wong, Keung Li, & Tseng, 2016).

2.4.1 Differences between PTW and car driving behaviour

Car drivers' behaviour is different from that of PTW riders. Cars follow one after another keeping a 'lane-discipline' (Cho & Wu, 2004) and the lateral movement is mainly due to the lane change. Motorcyclists need less space to move themselves and often perform "non-lane-based" actions and trajectories, e.g. zigzag movements or filtering the traffic (Nguyen, Hanaoka, & Kawasaki, 2012). For example, taking advantage of the smaller size, on straight sections of urban carriageways, PTWs mostly use lanes when traffic flow is fluid and overtake in the space between lanes when traffic is congested (Hublart & Durand, 2012). PTWs take advantage of their manoeuvrability in congested traffic situations to filter through the available space between vehicles and move to the front of the queue (Fan & Work, 2015; Nair, Mahmassani, & Miller-Hooks, 2011). PTW users may also filter between lanes for safety reasons so that, depending on the behaviour of other users, they can move over into one lane or another and also see better and anticipate manoeuvres (Hublart & Durand, 2012). Consequently, motorcycles could potentially 'show up' from some unexpected locations, representing safety concerns, as frequently other vehicles fail to detect the presence of PTWs in the traffic.

Several studies have attempted to understand the filtering behaviour of PTWs in heterogeneous traffic streams. (Bonte, Espié, & Mathieu, 2007) proposed a multi-agent solution for two-wheeled vehicles to reproduce behaviours specific to them, such as driving between cars. (Vlahogianni, 2014) evaluated the factors that significantly affect PTW riders' decision to accept critical lane widths during filtering. Critical lane width is defined as the minimum lateral clearance between any two vehicles, which most of the PTW riders uses

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while filtering. Some of the parameters that influence riders' decision are relative speed, spacing, heavy vehicles' presence and occurrence of platoon of moving PTWs.

Additionally, there are some differences in dynamic characteristics because of high power-to-weight ratio (i.e., speeds and accelerations of the vehicle types) and in area occupancy (i.e., size). The speed of a car in heavy traffic and at urban intersections is lower than that of a motorcycle or scooter (Walton & Buchanan, 2012; Lee, Polak, Bell, & Wigan, 2012). The capability of PTWs to make quick lateral manoeuvres leads to a shorter longitudinal and lateral separation than other classes of larger vehicles such as passenger cars (Walton & Buchanan, 2012; Amrutsamanvar, Muthurajan, & Vanajakshi, 2021)

Concerning area occupancy, generally, most existing simulation tools assume that the positioning of vehicles on a road results from the existence of physical lanes. However, this modelling does not simulate observed space occupation phenomena of motorcycles and scooters based on dynamic virtual lane-based movements. Very few studies on multi-agent traffic simulations apply the actual area occupancy behaviour of the PTWs. Different models based on microscopic data, collected from field video images in cities in Vietnam, defined the dynamic lane width of motorcycles with a minimum lateral distance of 0.8 m (Minh, Sano, & Matsumoto, 2012) and the lateral distance of the threshold safety space of 1.8 m on average for two vehicles driving side by side (Nguyen, Hanaoka, & Kawasaki, 2014).

2.4.2 SMoS for car-PTWs interactions

The classification of SMoS for motor vehicle perspective from Section 2.3.2 with time-based, evasive action-based and distance-based metrics (TTC, DRAC, PICUD…) can also be applied for PTWs. Those metrics are valid to measure the interaction between users that must share the same road (including PTWs). Yet, the differences between cars and PTWs noted in the previous section, mean that the appropriate thresholds and the severity risk models used for car-PTW interactions will differ from those of car-car interactions.

Currently, very few studies have measured the risk severity of traffic-conflict with PTWs vs. other road users, and most of them are focused on defining thresholds of parameters associated with near misses or crashes (Vlahogianni, Yannis, & Golias, 2013; Guo, Sayed, & Zaki, 2018) and loss of control (Attal, Boubezoul, Oukhellou, Cheifetz, & Espie, 2014; Huertas-Leyva, Savino, Baldanzini, & Pierini, 2020) without a SMoS to assess the potential risk of different interactions with other vehicles in real-time. Evasive actions-based SMoS typically involve powerful braking, speeding, or sudden swerving. As such, they can be simplified to either a significant change in speed or direction. Evasive actions-based SMoS for PTWs were analysed in cities of China using as independent variables evasive action-based indicators such as TTC, yaw rate and jerk extracted from video-based computer vision techniques and three levels of risk categorized by experts as dependent variable (Guo, Sayed, & Zaki, 2018; Tageldin, Sayed, & Wang, 2015). The latter studies concluded that in less organised environments with a high frequency of interactions between different types of road users, indicators of temporal proximity on their own may not work very well. The limitations of time-based SMoS for PTWs without other indicators (e.g., deceleration information) were investigated in case study in China (Tageldin, Sayed, & Wang, 2015). This

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study determined that evasive actions-based SMoS had greater potential for identifying motorcycle conflicts in highly mixed and less organized traffic environments than time-based SMoS, such as time to collision.

Studies focused on distance-based SMoS for PTWs are relevant since safety gaps of motorcycles were observed to be smaller than those of cars (Amrutsamanvar, Muthurajan, & Vanajakshi, 2021; Lee, Polak, Bell, & Wigan, 2012; Nguyen, Hanaoka, & Kawasaki, 2012). Distance-based SMoS developed with simulations and calibrated with data from video-clips have been used to evaluate motorcycle traffic conflicts related to sudden braking using the 'safety space' concept on straight segments of congested urban roadways of Ho Chi Minh (Nguyen, Hanaoka, & Kawasaki, 2014). The contribution of PTW speed in fatal accidents was studied in a parameter space for considering the accident risk and accident severity dimensions provided by the speed-squared versus stopping distance domain (Murphy & Morris, 2020), but this mainly applied to see the effects on the severity of real fatal crashes and not in traffic conflicts. Lee at al. (2012) defined the safety gap as the longitudinal spatial distance between the front edge of a following vehicle and the rear edge of its preceding vehicle. They found that the headways of those motorcycles located in the right differed from those in the left half areas behind the preceding cars. The possibility to faster lateral speed (swerve) and to require a shorter lateral movement if positioned behind left/right side of the bottom of the leading vehicle makes that for PTWs may allow a lower safety gap than other vehicles such as cars. Consequently, the same risk-metrics in car-following cannot be applied for PTWs and cars.

2.4.3 Recommended SMoS for PTWs

As commented previously, for urban scenarios a few studies were found to give recommendations for SMoS for PTW interactions. Considering the few studies analysing the severity risk of the PTW-car interactions, methods estimating the Crash Potential Index (CPI) from studies of vehicles interactions (not specific for PTWs) may be adapted for PTW-car interactions. Wang and Stamatiadis (Wang & Stamatiadis, 2014; Wang & Stamatiadis, 2013) proposed a CPI method (called crash propensity metric by the authors) to estimate the crash probabilities of three types of traffic conflicts between vehicles at intersections (crossing conflict, lane-change conflict, rear-end conflict). They conducted an experimental validation by simulating 12 four-leg signalized intersections along three arterials in Kentucky through a simulation package. As an example of the method, during a rear-end conflict, two situations were expected. First situation, during the traffic conflict Time-to-Collision (TTC) the rider brakes and the vehicle performs as expected with more than the minimum required braking rate (RBR) and avoids the crash. Second, the vehicle fails to perform as expected and does not meet the RBR, so the conflict turns into a crash. The CPI considers multiple factors such as time, speed, reaction time, and braking rate, which are able to identify the safety critical scenarios that TTC alone cannot detect. In order to use a Crash Potential Index as SMoS for PTWs for urban scenarios, threshold values for several other SMoS threshold values are required. As presented in Section 2.3.3 for car-car interactions, Table 3 shows information about threshold values for different metrics found in the literature mostly

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focused on PTWs. A more complete description of severity metrics for various scenarios is presented in Table 6 in the appendix.

Table 3: Threshold values for recommended severity metrics with PTW interaction

Metric	Threshold	Source	Scenario
TTC	≤1.5s	(Tageldin, Sayed, & Wang, 2015; Wang & Stamatiadis, 2014)	Urban
Desired braking deceleration (average)	left-half area: -4.12m/s2 right-half area: -4.04m/s2	(Lee, Polak, Bell, & Wigan, 2012)	Congested Urban, car-following/rear-end
MADR dry conditions	Range Novice-Expert [3.83-8.03m/s2]	(Huertas-Leyva, et al., 2019)	Urban, PTW straight
Reaction Time	0.75s 0.5 s	(Lee, Polak, Bell, & Wigan, 2012) (Nguyen, Hanaoka, & Kawasaki, 2012)	Car-following/rear-end Lane-Change: (including side-swipe)
Safety gap distance (average; SD)	Longitudinal gap: 7.00m (0.32) for the left half 5.42m (0.34) for the right-half Longitudinal gap: 8.1m (3.64) Safe lateral distance: >1.8m	(Lee, Polak, Bell, & Wigan, 2012) (Amrutsamanvar et al., 2021) (Nguyen, Hanaoka, & Kawasaki, 2012)	Congested Urban, car-following/rear-end (avg. speed 36km/h) Congested Urban, car-following/rear-end (avg. speed of traffic stream 20km/h) Congested Urban
Crash Potential Index (CPI)	Low severity: CPM < 0.10 High severity: CPM > 0.90	(Wang & Stamatiadis, 2013, 2014)	Urban, car-following/rear-end

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2.5 VRU Perspective

This section focuses on VRU-traffic interactions, with the central goal to identify relevant description metrics for safe and unsafe behaviour of VRUs. When it comes to such SMoS for VRU-traffic interaction the literature available reveals a low level of maturity. For instance, in 2016 the EU Project InDeV (Laureshyn, et al., 2016) presents recent insights into the topic by putting upfront that it may be exhausting to gain a clear overview of the current state of the art. The authors state that the literature is vast and diverse, hard to reach, and one may run the risk to focus on technical improvements in this area, while neglecting human factors (Laureshyn, et al., 2016).

To deal with the issues raised in InDeV and to enrich existing work, we choose a complementary approach in SAFE-UP. For the identification of description metrics for VRU-traffic interactions, it could be useful to focus not only on the observable behaviour of VRUs (e.g., TTC, PET), but to consider the emergence of VRUs' behaviour as well (Liu, et al., 2012). From a psychological perspective, human behaviour is the result of cognitive information processing which can be broadly described via the three stages Perception Cognition Action (and its output and feedback); cf. (Proctor & Van Zandt, 2008; Kuligowski, 2009). The result of VRUs' perception and cognition processes are likely to determine the activation, selection, and conduction of responses (action stage). More specifically, the VRUs' perception and subjective interpretation of a situation (perception stage) lead together with an internal matching with memory stages, and the interpretation of potential risks (Kuligowski, 2009) to an understanding of the respective situation and an emotional state (cognitive stage). Recent research has shown that processes in this cognitive stage do not exclusively depend on aspects of a singular situation (such as an approaching vehicle), but on the accumulation of recent experiences (Dittrich, 2020). Hence, depending on the recent past, two similar situations can lead to a different understanding and valence (or in other words, the probability for a certain understanding and emotional state is different). The outcome of the cognitive stage together with the VRUs' individual characteristics are key to the VRUs' behaviour (action stage). They set the probability for an (un-) safe behaviour in a given situation. This is why measures of the perception and cognition stage appear to be important description metrics for VRU-traffic interactions when setting up a traffic simulation including VRUs and their probable behaviour.

Participant studies enable the direct assessment of VRUs' subjective evaluations as well as the resulting objective behaviours and are, therefore, good sources for the compilation of such measures. For this purpose, IKA conducted a literature review on (mostly empirical) studies with regard to VRU-traffic interactions. In line with argumentation of InDeV and underlining the novelty of this bottom-up approach from IKA, the key word "Surrogate Measures of Safety" was not mentioned in these empirical studies (apart from one (Liu, et al., 2012)). The most promising studies (selection criteria mentioned in appendix A) were analysed in detail and are being described briefly in the same appendix. The conclusions with regard to possible description metrics for VRU-traffic interactions along the information processing paradigm (perception, cognition, and action) that are assumed to influence the

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probability for an (un-) safe behaviour are depicted in the following section. Please note that the measures of the stages perception and cognition originate from human factors research and thus differ from conventional computational variables of traffic simulations. The transfer into computable variables is one of the steps planned to be conducted in SAFE-UP.

2.5.1 Description metrics for VRU-traffic interactions

The references of the studies reviewed are depicted in Table 4.

Regarding the individual's understanding of a traffic situation at the perceptual and cognitive stage, the literature review implies that the psychological constructs *perceived risk*, *perceived criticality*, *perceived comfort*, and *subjective understanding of the traffic situation* are relevant for VRUs' subjective evaluations and hence could serve as description metrics (see Table 4). These constructs were mostly assessed via short self-formulated questionnaires or open questions regarding the participants' (self-estimated) behaviour and their reasoning for this. Furthermore, the emotional state that results from a given situation, e.g., the *level of frustration,* can influence the VRUs' behaviour and, therefore, can be understood as a description metric for the cognitive stage as well. As mentioned above in section 2.5, both, the understanding and emotional valence of a traffic situation should be regarded in an interplay with other factors. Namely, these VRU description metrics seem to be highly influenced by the *traffic situation*, other subjective dimensions, such as *distraction*, *habits, safety beliefs,* as well as *subjective norms,* socio-demographic factors, such as *age*, *experience* and *incidents in the past* (Abadi, Hurwitz, & Macuga, 2019; Dittrich, 2020).

Physiological responses, such as *heart rate,* could serve as objective description metrics. Regarding the probable VRU-behaviour at the action stage, objectively quantifiable metrics are e.g., the *lateral trajectory, reaction time (i.e., time to desired behaviour), speed reduction, gaze behaviour/ fixation time of potential hazard,* or *aggressive behaviour* (see Table 4).

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Table 4: Description metrics for VRU-Traffic interactions derived from the twelve studies.

Stage of metric	Description metric	Category	Study number (See Appendix/ Source)	Scenario
Perception and cognition	Perceived risk	Evaluation of situation (subjectively measured)	8,9 (Kovácsová, de Winter, & Hagenzieker, 2019; Doorley, et al., 2015)	Urban
	Perceived criticality		1 (Oron-Gilad & Meir, 2020)	
	Perceived level of Comfort		10 (Abadi, Hurwitz, & Macuga, 2019)	
	Understanding of the situation		2, 3 (Tabibi & Pfeffer, 2003; Habibovic & Davidsson, 2012)	
	Frustration	Emotional state	12 (Dittrich, 2020)	All
Action	Heart rate	Physiological values	9 (Doorley, et al., 2015)	Urban
	Lateral trajectory (cyclists only)	Behaviour of VRUs (objectively measured)	7 (Abadi M. G., Hurwitz, Sheth, McCormack, & Goodchild, 2019)	
	Reaction time, i.e. time to desired behaviour		1, 5 (Liu, et al., 2012; Oron-Gilad & Meir, 2020)	
	Speed reduction		7 (Abadi M. G., Hurwitz, Sheth, McCormack, & Goodchild, 2019)	
	Aggressive behaviour		12 (Dittrich, 2020)	All

To clarify the measures listed in Table 4 in terms of their possible contribution to estimate the probability of VRUs' (un-) safe behaviour, every description metric is explained briefly in the following in chronological order of the table:

The levels of *perceived risk*, *criticality, comfort, and understanding of a traffic situation* serve as indicators to determine the probability for a certain evaluation of and, thus, a certain behaviour in a traffic situation. The level of *frustration* has the potential to increase the occurrence of *aggressive behaviour*. The prevalent *heart rate* can be an indicator for the

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equivalent arousal level in a safety-critical situation. It is to be expected that the *lateral trajectory* of a cyclist is a potential cue for a risk mitigating behaviour (i.e. evasive trajectory). A fast *reaction time* indicates a quick response to a hazard. A fast *speed reduction* can be a risk mitigating behaviour or a reaction to a hazard while a slow *speed reduction* can be a cue for an ongoing attention process/ understanding of the traffic situation. *Gaze behaviour/ fixation time of a potential hazard* could serve as indicator if a hazard has been identified or not. This in turn has the potential to determine, if a risk mitigating behaviour is to be expected.

As indicated at the beginning of the section, VRUs' recent experiences (e.g., multiple cutting off or a sequence of red traffic lights) can potentially influence the VRUs' understanding of a situation and emotional states (e.g., level of frustration) and, thus, can modulate the probability of (un-) safe behaviours (an aggressive reaction in a low safety critical situation, which in turn can cause a safety critical situation) (Dittrich, 2020). This interplay is not assessed sufficiently yet and, therefore, not implemented in Table 4. Nevertheless, we assume that VRUs' behaviours are based at least in parts on external reasons and only a holistic approach can lead to a deeper understanding with regard to the probability of (un-) safe behaviour (Liu, et al., 2012). A holistic view to better understand (non-) safety critical VRU-traffic interactions would, therefore, include at least:

(a) the role of external/ situational factors on the probability of both, a certain emotional state and an understanding of a situation, and

(b) the role of these on the probability of a certain behaviour.

Further empirical research is needed in this holistic approach to define situation-dependent description metrics and SMoS for VRUs, so that the listed metrics can be transferred into computable metrics of traffic simulations. In D2.6 (use case definition and initial safety-critical scenarios) of SAFE-UP some of the mentioned aspects will already be tackled based on literature research. In Sections 3.2 and 4.3, IKAs' plans to tackle the open questions are briefly outlined.

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3. Partners’ Contributions to the State of the Art

As mentioned in Section 1.2, this chapter presents each partner’s initial research and development plans for T2.2. These plans are inspired by areas in the state of the art (SotA) that are not well covered. The focus area of each partner is shown in Figure 3.

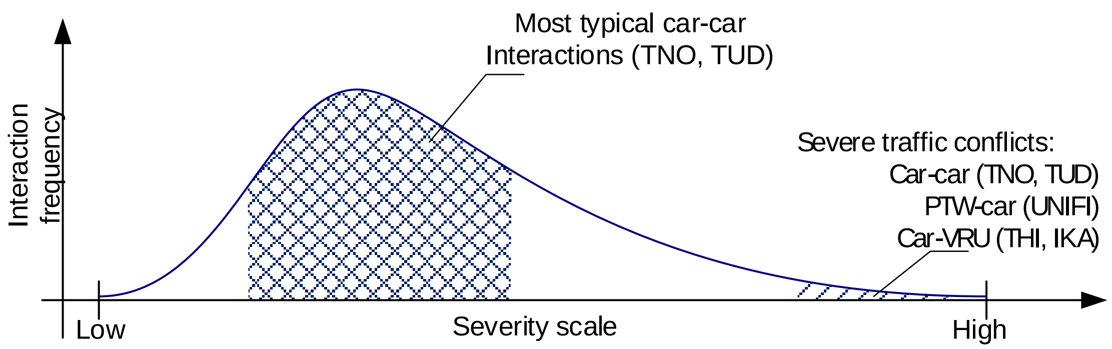

Figure 3 Overview of the positioning of the research work by T2.2 partners.

3.1 IDIADA

In T2.2 IDIADA will process information provided by T2.1 and help define metrics for assessment of safety-critical scenarios considering all traffic participants. This activity is expected to start in September of 2021, after T2.1 completes its work.

During the first months of T2.2 resources had been dedicated to understand the needs and requirements for the definition of the metrics. While doing this activity it was noticed the need to obtain better NDD. On the other hand, jointly with T2.1 it was detected the need to create a common activity to align the needs between T2.2 and T2.1 regarding NDD needs.

The first step was to create a template so the partners from T2.2, T2.3 and from other WPs could explain their needs regarding NDD. This process is ongoing. Once the information is collected, T2.1 will be able to check if the databases in which they are working on can provide the needed input or if it will be necessary to define another NDD activity to cover specific needs of the partners.

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3.2 IKA

Surrogate measures of safety (SMoS) are being utilised to investigate and quantify traffic safety (Laureshyn, et al., 2016; Liu, et al., 2012). As these measures are according to InDeV not based on accident data they are referred to as “surrogates” and introduced to be complementary to accident records. The literature discusses this approach as advantageous in terms of time-efficiency, ethics, informational content, and accurateness (Svensson A. , 1998; Hydén, 1987). Today, SMoS help to characterise relevant conditions as well as frequencies of occurrence of conflicting events and are, therefore, utilised as approximation for the probability of collisions, mainly regarding car-to-car interactions.

When it comes to SMoS for VRU-traffic interactions, however, the literature available reveals a different level of maturity and former work has already pointed at the risks to focus on technical improvements in this area, while neglecting human factors (Laureshyn, et al., 2016). This is where IKA sees the potential to take over a complementary perspective on SMoS for VRUs.

As outlined in the introduction of the present deliverable, traffic interactions are very frequent whereas traffic accidents appear to be comparably rare. Although not each traffic interaction leads to an accident, some interactions seem to be more severe than others and some lead to collisions. This motivates the hypothesis that crashes result from a temporal sequence of events in which conflicting events occur prior to a crash event (Laureshyn, et al., 2016).

Since conflicts and collisions tend to share a common continuum of events, the frequency of subjectively perceived and negatively evaluated events can be used to predict those of high-severity events (Dittrich, 2020). This approach deviates from the usage of well-known SMoS, i.e. those established for car-to-car interactions, such as TTC or PET. Instead, IKA puts VRUs and their ability of cognitive information processing in the focus of its work. In this vein, ika follows up on the hypothesis that human beings perceive their environment via a cognitive filter (Wickens, 2015) letting only pre-selected information pass over to the cognitive stage. Here, (depending on the nature of the information) higher/lower cognitive processing will result in a subjective understanding of and an emotional state regarding the information perceived and finally, lead to an observable response (action) (Proctor & Van Zandt, 2008). In others words, IKA pursues the approach by Dittrich (Dittrich, 2020) that human behaviour in traffic is being moderated by the occurrence, frequency, as well as subjective evaluation of events on a temporal and spatial basis. This approach sheds light on a novel aspect in SMoS research, as the interplay of the variables occurrence and frequency together with the subjective evaluation of events experienced will be used as variables for probability functions to predict (un-)safe VRU behaviour in a traffic simulation. In order to derive these probability functions via regression analyses, IKA will conduct an empirical study (T2.3) to research (a) the role of external events (e.g., nature, frequency, spatial and temporal resolution) on the probability of a certain subjective evaluation (e.g., level of frustration, comfort etc.) and (b) the role of this on the probability for (un-) safe human behaviour (e.g., inappropriate steering or acceleration habits, ignorance of traffic rules).

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Based on the hereof resulting probability functions, the derivation of SMoS for VRUs and their usage in respective micro-simulations is the anticipated next step.

IKA's research is planned to be done in lab experiments using a VR pedestrian and bicycle simulator setup. IKA will focus on subjective and objective data. In a nutshell, this systematic approach will support the development of the simulation model of SAFE-UP and is aimed at an increased level of accuracy of VRU description metrics.

3.3 THI

THI proposes an approach to integrate common SotA technics with novel methods into a new risk assessment framework. This framework will also introduce a new measure of risk based on artificial risk field theory. This risk artificial risk field will be composed of a prediction module for dynamic objects and a crash severity estimation module. The product of interaction likelihood (prediction module) and interaction severity (crash severity estimation module) will be the risk measure. Which is another metric to measure the interaction severity. Most SotA system designs only consider collision avoidance but not the case of unavoidable collisions.

Here, THI will contribute to the crash severity estimation, which in turn can cover the case of an unavoidable collision. The advancements to SotA will include the propagation of uncertainty values to increase the robustness of the overall system design. Another feature will be continuity to increase robustness for numerical solving further. Also, such a system will be built to satisfy scenarios beyond the scope of SAFE-UP. To evaluate the crash severity, metrics from potential injury indices are derived. Typical metrics are occupant load criterion, frontal crash criterion, and acceleration severity index. To derive those values, THI focuses on investigating data-driven as well as deterministic approaches. The exact approach will be chosen during the development phase based on the selected scenarios and needs of the other SAFE-UP partners.

The chosen approach to introduce an uncertainty-aware crash severity estimation algorithm then integrates well to generate a general-purpose risk measure based on potential field theory.

3.4 TNO

TNO focuses on two areas

- Development of methods to identify the most typical driving interaction from driving data
- Development of a severity metric for driving interactions that is context-dependent.

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3.4.1 Typical driving interactions

As shown in Figure 2, the vast majority of driving interactions carry low severity. The relationship between driving interactions and severity is context-dependent. That is, it varies with the type of location, time of day, weather conditions, etc.

Thus, there is a need for a generic method to characterize typical driving interactions based on recorded data from specific contexts, which allows one to differentiate between a *safe driver* and an unsafe one.

We propose to develop one such method based on machine learning (ML) algorithms trained on publicly-available naturalistic driving data, such as NGSIM (USDOT, 2006). The method would allow one to represent the most typical features of driving interactions withing a trained ML model, and then used it to classify new interactions as typical or a-typical using an anomaly detection approach.

This work will be an improvement over our initial efforts (Tejada, Manders, Snijders, Paardekooper, & de Hair-Buijssen, 2020) by improving the original ML algorithm and applying it to urban driving data.

3.4.2 Context-dependent Severity Metric

As mentioned above and shown in Section 2.3, most severity metrics currently available are based on explicit formulas that relate the kinematic variables of interacting vehicles. These formulas are not context-dependent. Generally, they rely on assumptions about driver behaviour (e.g., instant reaction times) and how traffic participants drive (e.g., constant speed). That is, they do not directly reflect specific driving conditions at specific locations.

Thus, we propose to develop a method to replace such assumptions in known severity metrics with data-driven models of the variations in drivers and traffic participant behaviours. An initial version of this approach will be based on highway driving data from datasets such as NGSIM.

3.5 TUD

During on-road driving, the surrounding traffic environment, especially for the surrounding vehicles, can vary dynamically. The car-car SMoS, which are defined based on the predicted motions of interacting vehicles, are suitable for this purpose, i.e., they can be calculated at each moment during an encounter. However, the subject vehicle, is not certain about the future motion of its neighbouring vehicles and consequent crash outcome. Uncertainty, therefore, is an inherent component of the driving risk estimate. SMoS do not typically account for this uncertainty. They assume a deterministic future motion, i.e. motion with unchanged velocity/acceleration.

The artificial potential field is a prominent paradigm used to tackle vehicle and robot navigation (Dunias, 1996). The attractive feature is that it allows the vehicle to autonomously

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navigate using only its location and local sensor measurements. In this paradigm, an obstacle to the vehicle is modelled as a repulsive potential field (or risk field). The vehicle can use the field gradient at its location to generate control actions to navigate while avoiding the obstacle. A field paradigm was initially employed to model driving risk accounting for the influence of driver, vehicle and road characteristics (Wang, Wu, & Li, 2015). Later, this model was extended and applied in a rear-end crash avoidance system (Wang, Wu, Zheng, Ni, & Li, 2016). However, the model cannot be directly used for traffic safety analysis, as it is not objectively formulated using factors correlated to crash statistics. Therefore, the artificial potential field theory offers a paradigm to develop a generic driving safety assessment (Mullakkal-Babu, Wang, Farah, Arem, & Happee, 2017). Using the paradigm of artificial field theory, in this project, we will present an approach to assess the driving risk of an individual vehicle. The driving risk estimate constitutes a crash severity term and a collision probability term. To estimate the collision probability, the subject and neighbouring vehicles possible positions and associated probabilities at discrete future time steps are predicted.

Moreover, we will develop a neural network based two-stage multi-modal prediction model, consisting a lane-change prediction module and a trajectory prediction module. The lane-change prediction model is first invoked and its output is then used as input for the multi-model trajectory prediction model, which can provide more accurate prediction results in terms of different evaluation metrics. The prediction model will be integrated with the probabilistic collision-based safety assessment framework. The effectiveness and computational efficiency of the integrated safety assessment framework will be validated using existing NDD as well as simulations. The proposed safety assessment framework is promising to further provide guidance for vehicle motion planning.

3.6 UNIFI

Current modelling approaches cannot explicitly group filtering, overtaking, oblique following, swerving and tailgating manoeuvres of PTWs in a single model (Das & Maurya, 2018). Literature shows, that although some PTW riding behaviour models have been developed giving insights about the riding behaviour for specific manoeuvres, almost no metrics are available to determine the severity risk of the different interactions among PTWs and other road users. A point to consider is that a minor proportion of the few studies on riding behaviour model have been investigated on traffic scenarios of countries of developed economies with passenger cars being predominant and characterized by a more ‘homogeneous’ traffic than that of developing economies where frequently traffic is composed of a wide variety of vehicle types which frequently occupy the same right of way (Kiran & Verma, 2016). The effect of cultural differences in traffic behaviour may affect the effectivity of traffic conflict techniques (Tiwari, Mohan, & Fazio., 1998; Tageldin, Sayed, & Wang, 2015), thus, significant differences may occur between behaviour models and SMoS belonging to PTW-dominated traffic (70% PTWs) more frequent in Asian cities or passenger cars-dominated traffic (e.g., European or North American cities). This makes even more necessary to study traffic interactions in scenarios from developed countries where

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autonomous car use is expected to be deployed earlier. A better understanding of the unique patterns of interaction of PTWs with other road users will help to develop better simulation models capable of measuring the risk of traffic conflicts. Realistic models of mixed traffic conditions must faithfully address the interaction of cars with VRUs, such as PTWs.

Previous research has demonstrated that the driving behaviours of riders on PTW's significantly differs from that of car drivers (safety gaps, trajectories, speeds…) that are more present in traffic interactions related to lane-sharing, tailgating or overtaking in multimodal rural environment (Barmpounakis, Vlahogianni, & Golias, 2016; Das & Maurya, 2018). The behaviour of motorcycle drivers on highways, however, seems to be less different from that of cars, so early research should prioritize understanding behaviour in urban environments in order to model traffic simulations more realistically. Very few studies have measured the risk of traffic interactions with PTWs involved. The main limitation for this type of studies is the need for extensive naturalistic driving data (Barmpounakis, Vlahogianni, & Golias, 2016) and, in contrast, so far there is very few naturalistic driving data involving PTWs.

The SAFE-UP approach is to develop an integrated model to assess the traffic-conflict of motorcycles and mopeds in urban roads. We aim to develop an integrated model to assess the traffic-conflict of motorcycles and mopeds in urban roads, the target scenario consists of tailgating issues and rear-end conflicts in urban road. The proposed risk metric will be unique for motorcycles and will include new features developed with a concept of time proximity indicator (Time Headway / Distance Headway) and evasive action-based (based on kinematics-based measures: e.g. yaw and roll rate and deceleration) indicators for evaluating the severity of powered two-wheeler (PTW) conflicts. The Surrogate Safety Metrics will be developed using naturalistic data collected in urban area. Initially our risk metric will estimate the severity of events in traffic, mainly for events involving vehicles moving in the same direction than PTW. We will introduce a new measure of risk based on probabilistic models of crash outcome severity for real-time safety prediction, identifying those safe interactions, and consequently quantifying potential risk scenarios by detecting deviation from defined safe riding.

Two different approaches with two different datasets will be used to derive the surrogate safety metrics. First approach will use naturalistic data collected by a PTW (local view) to code the traffic conflicts including severity (critical, safe) with the observation of the videos, then will develop the severity metrics based on extreme events by making the best use of observed 'maximal' data with the variables from video-coding and the kinematics-based measures (e.g., steering rate, yaw rate, deceleration, jerk…). The second approach will use bird's-eye view naturalistic data using the spacing with traffic mix, speeds and type of road user as factors of the real-time safety metrics. In both approaches a validation subset of the naturalistic data will be used to assess the performance of the risk metrics.

Risk metric will also include the severity of the collision avoidance required, using the frequency distribution of braking from naturalistic data. If the number of near-miss cases from naturalistic data is limited, UNIFI will examine the Maximum Available Braking Rate (MABR) and the distribution using their data on emergency braking performance in field experiments with different levels of riders (Huertas-Leyva, et al., 2019). The conflicts

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selected in our study will be those rear-end with braking as the main evasive manoeuvre, assuming that adjacent gap is rejected to perform a lane-change manoeuvre. Additionally, work exploring risk-based trajectory generation and decision making for straight road segments to assess risk conflicts during lane change manoeuvres can be considered. To assess the generalization of the results for different datasets, the risk severity models developed may be validated with the car-PTW interaction collected by IDIADA in urban scenarios.

4. Conclusions & Recommendations

4.1 Motor Vehicle Perspective

The literature review performed for car-car interactions revealed that there is an abundant number of SMoS for quantifying the severity of car-car interactions both in highway and urban scenarios and for various types of collisions. The most recommended set of metrics to identify critical interactions in simulations are listed in Table 2. A more complete list of metrics that provides formulas for each metric and the scenarios they apply to is given in the appendix in Table 5. This table also includes recommended threshold values for various combination of metrics and scenarios.

Despite this abundance of SMoS, challenges still remain in applying them for safety evaluations. One of such challenges is the choice of threshold values for the metric. In literature, there is no consensus on threshold values. The practice is usually to give a range for the threshold value. This means that a scenario may be considered critical for a specific threshold value and not critical for another threshold. This makes it difficult to conclude with much certainty whether a scenario is critical or not based on one threshold value of a metric. Therefore, methods to determine the most appropriate threshold value of a metric for a specific scenario are needed. Another way to circumvent the threshold issue is to develop methods for identifying critical situation which are threshold-independent. This alleviates the need to choose a specific threshold.

Another challenge in applying SMoS is the selection of an appropriate metric for a particular scenario. In most cases, one metric is usually not enough to classify a scenario as critical or not. In addition, not all metrics are defined for all driving situations. A classic example is TTC, which is only defined for cases where the follower is faster than the leader. This means that for such situations, a different metric needs to be used. Finally, it is possible that the conclusions made by one metric may contradict the one made by another metric. So, a situation defined as safe by one metric can be considered critical by another metric. This poses a challenge in reaching a conclusion about the criticality of the situation. One way to overcome this challenge is to use an ensemble of metrics for analysing a scenario and then make a more informed conclusion on criticality by taking into account the conclusions from all the considered metrics. Another way is to derive a single metric which captures the properties of several metrics.

Further, it is important to remark that most severity metrics are geared to identify critical driving interactions. Little work has been done on identifying and recognizing safe driving interactions. Such capability is important to prescribe how vehicles should drive in order to avoid engaging in critical interactions. There is a need to develop data-driven severity metrics that do not rely on a-priori assumptions of driver or vehicle behaviour, but on context-dependent behaviours.

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Besides, uncertainty is an inherent component of the driving risk estimate. SMoS do not typically account for this uncertainty. They assume a deterministic future motion, i.e. motion with unchanged velocity/acceleration. Using the paradigm of artificial field theory, in this project, we aim to present an approach to assess the driving risk of an individual vehicle. The driving risk estimate constitutes a crash severity term and a collision probability term. To estimate the collision probability, the subject and neighbouring vehicles possible positions and associated probabilities at discrete future time steps are predicted. Moreover, an interactive intention prediction model based on machine learning approaches is integrated to better represent the future vehicle reachable space. Eventually, the established safety metric is applied to classify interaction severity, and further provide guidance for motion planning.

4.2 PTW Perspective

Literature review has showed that behaviour of powered two-wheelers (including interactions with other road user) differs from that of car passengers, and that specific SMoS for PTW are necessary for a complete assessment of the interaction of cars (and eventually autonomous cars) with the rest of road users in the traffic environment. An overview of currently available SMoS for car-PTW interactions can be found in Table 6, and list of recommended metrics to identify critical car-PTW interactions in simulations are listed in Table 3.

SAFE-UP will use real-life urban scenarios to define SMoS specific for PTW-car interactions, modelling the scenario parameters with fitted distributions (e.g., Kernel Density Estimations) collected from the key parameters of naturalistic driving. During T2.2 we will define safety space to describe the non-lane-based movements unique to motorcycles. New features will be also developed for traffic conflict assessment such as parameters of acceleration and deceleration, and the conditions for choosing a lead vehicle. Additionally, in this work, the surrogate severity metric will be used to directly extract simulated conflict data from trajectories files generated from microscopic traffic simulation. The probability of ending a traffic conflict with a crash will be estimated based on simulations. The simulation will generate test cases with traffic conflicts between cars and PTWs with the purpose to identify the scenarios where high severity metrics are more frequent.

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4.3 VRU Perspective

As outlined in existing work, e.g. in the EU project InDeV (Laureshyn, et al., 2016), the maturity level of SMoS for VRU-traffic interactions is low and respective literature is vast and diverse, hard to reach, and one may run the risk to focus on technical improvements in this area, while neglecting human factors. Therefore, IKA implemented a complementary approach and conducted a literature research with a focus on empirical studies on human factors (section 2.5 and Appendix A) which will be the basis for IKA's future works in SAFE-UP. This alternative approach in the literature research was conducted to include preliminary work regarding the preceding causal chain for resulting VRU behaviour and not limit the research to observable factors of a traffic situation. It allowed to gain insights on subjective and objective description metrics for (non-) safety critical traffic situations of VRU-traffic interaction (VRU perspective). Whilst each description metric (Table 1) has the potential to serve as predictor for human behaviour, the interplay of these metrics is hypothesised to be promising for increasing the accuracy of computational modelling of VRU-vehicle interactions. Applying psychological models of human information processing, the probability for a certain VRU-behaviour (i.e. objective behavioural data) is the result of two preceding stages (perception and cognition). The hypothesis is that objective data alone can be regarded as a limited predictor due to missing information on the relevant question "why do humans behave as they do in certain situations?". Perception and cognition are not observable and, therefore, considered to be latent. Nevertheless, both stages are the upstream process before it comes to observable human behaviour. Going one step further, recent events are known to influence subsequent traffic behaviour and future situations, respectively. E.g., traffic participants conduct aggressive (i.e. unsafe) behaviour due to their current level of frustration which in turn was caused by a chain of events in the traffic. In other words, it is to be assumed that knowing about the underlying reasons could contribute to the improvement of the probability estimation of human behaviour in traffic. Currently, the identified measures (Table 4) of the stages perception and cognition differ from conventional metrics of traffic simulations. To allow for a transfer into computational modelling on safety estimations, in T2.3 of SAFE-UP IKA plans to conduct an empirical participant study in a VR simulation setup. The results will feed into the simulation model of SAFE-UP and further deliverables (esp. D2.1, D2.6, D2.9 and D2.14).

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Appendix

Mapping SMoS with Scenarios

In this section, SMoS for both car-car and car-PTW interactions are mapped to scenarios. As discussed before, various SMoS are available in the literature for quantifying the severity of interactions. The choice of which metric to use depends on the scenario that is under consideration. For instance, some metrics are well-suited for car-car interactions during a car-following scenario on a highway while others are suited for crossing scenarios at urban intersections. There are also metrics which are suited for very dangerous situations like cut-ins or emergency braking of the lead vehicle.

The mapping is shown in Table 5 (car-car) and Table 6 (car-PTW), based on an adaption of the work in (Mahmud, Md, Hoque, & Tavassoli., 2017). These tables present the following information:

Column Name	Information Provided
Metric	This gives the name of the metric including the commonly used abbreviation as found in literature.
Description	This column gives a full definition of the metric. In general, for the selection of a metric, the scenario description should fit the description of the metric.
Formula	This columns gives the formula used for calculating the metric. It also includes a description of all the variables used in the formula. Before selecting a metric for evaluating a scenario, all variables defined in the formula should be checked whether they can be extracted from the scenario.
Thresholds	For a given metric, an attempt is made to give indicative values for the threshold of severity (i.e. values beyond which a situation is considered critical). The thresholds vary according to the scenario and the use case. It should be noted that threshold values are indicative and should not be taken as strict values.
Scenarios	This column gives a suggestion of scenarios for which the metric is suitable. Most metrics can be used for various scenarios while some can only be used for a particular scenario. The list of scenarios is thus non-exhaustive. When a scenario is defined, the description should be compared with the description of the metric to see if there is a potential match.

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Use Cases	Similar to the scenarios, this column attempts to match the metrics to the relevant use cases. Some metrics are suitable for highway or rural use case while others are suitable for urban.
Reference	For each metric, the relevant reference is given. To be concise, only a single reference is given for each metric. The chosen reference is the one that gives the most relevant information about the metric. In this reference, a description of the metric, formula and threshold can be found including references for the threshold values.

These tables should serve as guides for selecting the appropriate metrics for the scenarios under consideration.

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Table 5: Mapping of SMoS for car-car Interactions to scenarios

Metric	Definition	Formula	Thresholds	Scenarios	Use Case	Ref
Time-to-Collision (TTC)	The time until a collision between the vehicles would occur if they continued on their present course at their present speeds.	$\mathrm{TTC_i(t)} = \frac{\mathrm{X_{i-1}(t) - X_i(t) - l_i}}{\mathrm{V_i(t) - V_{i-1}(t)}}$ V: Vehicle speed X: Vehicle position l: ego vehicle's length $\mathrm{X_{i-1}(t) - X_i(t)}$: Relative distance $\mathrm{V_i(t) - V_{i-1}(t)}$: Relative speed	1- 2.0s for Approaches at intersections 1.6- 2.0s for Low level of conflict and less than 0.9s for high level conflicts 2.5s for supported drivers and 3.5s for non-supported drivers	Rear-end vehicle to vehicle collision, turning manoeuvres, crossing scenarios	urban, rural and highway	(Mahmud, Md, Hoque, & Tavassoli. , 2017)

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			3s for two-lane rural road 2-4.0s for urban road tunnels			
Time Exposed Time-to-Collision (TET)	Summation of all moments (over the considered time period) that a driver approaches a front vehicle with a TTC-value below the threshold value TTC	$TET_i = \sum_{t=0}^{N} \delta_i(t) \cdot \tau_{sc}$ $\delta_i(t) = \begin{cases} 1 & \forall 0 \leq TTC_i(t) \leq TTC^* \\ 0 & \text{otherwise} \end{cases}$ where, for a period $T = N \cdot \tau_{sc}$, there are N small time intervals, each interval is $\tau_{sc}(\text{e.g. } 0.1 \text{ s})$. $\delta_i(t)$ is a switching variable between 1 and 0 , and value 1 indicates a signal of risk condition, when the TTC value is below threshold TTC*.		Rear-end vehicle to vehicle collision, turning manoeuvres, crossing scenarios,	urban and highway	(Shi, Wong, Li, & Chai, 2018)
Time Integrated Time-to-Collision (TIT)	Integral of the TTC-profile during the time it is below the threshold	$TIT_i = \sum_{t=0}^{N} [TTC^* - TTC_i(t)] \cdot \tau_{sc}$ $\forall 0 \leq TTC_i(t) \leq TTC^*$ where, for a period $T = N \cdot \tau_{sc}$, there are N small time intervals, each interval is $\tau_{sc}(\text{e.g. } 0.1 \text{ s})$.		Rear-end vehicle to vehicle collision, turning manoeuvres, crossing scenarios	urban and highway	(Shi, Wong, Li, & Chai, 2018)

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Modified Time-to-Collision (MTTC)	Modified models which considered all of the potential longitudinal conflict scenarios due to acceleration or deceleration discrepancies.	$\text{MTTC} = \frac{-\Delta V \pm \sqrt{V^2 + 2\Delta a D}}{\Delta a}$ ΔV: Relative speed (m/s) Δ a: Relative Acceleration (m/s^2) D: Initial relative space gap (m);	Ideally the same threshold as TTC . The authors however propose 4s as threshold for severity.	Rear-end vehicle to vehicle collision, turning manoeuvres, crossing scenarios	urban and highway	(Ozbay, Yang, Bartin, & Mudigonda, 2008)
Crash Index (CI)	Influence of speed on kinetic energy involved in collisions.	$\text{CI} = \frac{(V_F + a_F \cdot \text{MTTC})^2 - (V_L + a_L \cdot MTTC)^2}{2} \times \frac{1}{\text{MTTC}}$ V_F: Following vehicle's speed (m/s); V_L: Leading vehicle's speed (m/s) a_F: Vehicle's acceleration (m/s^2) a_L: Leading vehicle's acceleration (m/s^2)		Rear-end vehicle to vehicle collision	urban and highway	(Ozbay, Yang, Bartin, & Mudigonda, 2008)
Time-to-Collision with Disturbance (TTCD)	TTC when a deceleration disturbance is applied to leading vehicle	$TTCD = \begin{cases} \frac{(v_1 - v_2) + \sqrt{(v_1 - v_2)^2 + 2d(l_0 - l_v)}}{d}, & d \leq \frac{2v_1 v_2 - v_1^2}{2(l_0 - l_v)} \\ \frac{2d(l_0 - l_v) + v_1^2}{2dv_2}, & d > \frac{2v_1 v_2 - v_1^2}{2(l_0 - l_v)} \end{cases}$ d: the deceleration rate of the leading vehicle d^*: the deceleration rate of the leading vehicle that causes the collision to occur exactly when the leading vehicle stops	In principle , the same thresholds for TTC can be used. The authors however recommend 1.7s to distinguish	Rear-end vehicle to vehicle collision, turning manoeuvres, crossing scenarios	urban and highway	(Xie, Yang, Ozbay, & Yang, 2019)

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		v_1: initial speed of the leading vehicle v_2: initial speed of the following vehicle (remains constant in the car following scenario) t_0: the time when a disturbance is given t^*: the time interval between the given of the disturbance and the full stop of the leading vehicle l_v: the length of the vehicle l_0: initial relative distance between the leading vehicle and the following vehicle l_1: distance travelled by the leading vehicle after being given a disturbance l_2: distance travelled by the following vehicle before colliding with the leading vehicle after a disturbance has been given to the leading vehicle	critical situations			
Headway (H)	The elapsed time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point	$$\mathrm{H} = \mathrm{t_i} - \mathrm{t_{i-1}}$$ $\mathrm{t_i}$: Time (vehicle i passes a certain location) $\mathrm{t_{i-1}}$: Time (vehicle ahead of vehicle i passes the same location).	Recommended safe headway is 2s in the US and most European countries. Swedish National Road	Rear-end vehicle to vehicle collisions	urban and highway	(Mahmud, Md, Hoque, & Tavassoli., 2017)

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			Administration recommends 3s for rural areas Minimum safe headway 0.7s 1.1s to 1.7s is considered comfortable <0.6s is considered dangerous.			
Time-to-Accident (TTA)	Time-to-Accident (TTA) is the time that remains to an accident from the moment that one of the road users starts an evasive action if they had	$$\mathrm{TA} = 1.5 \times \frac{V_i}{16.7 \times \exp\left(-0.0306 \times 0.5\ \mathrm{V_m}\right)}$$	Generally 1.5s is used to distinguish serious conflicts and it worked well for urban	Rear-end vehicle to vehicle collision, turning manoeuvres, crossing scenarios	Urban, Rural and highway	(Mahmud, Md, Hoque, & Tavassoli., 2017)

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	continued with unchanged speed and directions	V_i: initial speed V_m: Mean speed.	roads with low speeds. For rural roads with high speeds <1.5s is recommended			
Post-Encroachment Time (PET)	The time between the moment that a road user (vehicle) leaves the area of potential collision and the other road user arrives collision area.	$$\mathrm{PET} = \mathrm{t}_2 - \mathrm{t}_1$$ t_2 : Coming time at conflict point t_1 : Leaving time of conflict point.	Values between 1.0 to 1.5s are considered critical However, a study has found 6.5s to match well with aggregate crash data	Mainly crossing scenarios, lateral scenarios (merging / diverging)	Urban	(Mahmud, Md, Hoque, & Tavassoli., 2017)
Potential Index **for Collision**	Distance between the two vehicles considered when	$$\mathrm{PICUD(m)} = \frac{\mathrm{V}_1^2 - \mathrm{V}_2^2}{2\alpha} + \mathrm{S}_0 - \mathrm{V}_2\Delta\mathrm{t}$$	It is considered dangerous if	Rear-end vehicle collision, crossing	urban and highway	

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with Urgent Deceleration (PICUD)	they completely stop.	V_1, V_2: Velocity of leading car 1 and following car 2 , respectively S_0: Distance between car 1 and 2 Δt: Driver's reaction time 1 α: Deceleration rate to stop	the distance is <0	scenarios, Lane changes , emergency break by lead vehicle		(Shi, Wong, Li, & Chai, 2018)
Proportion of Stopping Distance (PSD)	Ratio between the remaining distance to the potential point of collision and the minimum acceptable stopping distance.	$$\mathrm{PSD} = \frac{\mathrm{RD}}{\mathrm{MSD}}$$ RD: Remaining distance to the potential point of collision (m) MSD: Minimum acceptable stopping distance (m).	Values <1 are considered dangerous	Collision with object		(Shi, Wong, Li, & Chai, 2018)
Unsafe Density (UD)	Level of "unsafe" in the relation between two consecutive vehicles on the road for a determined simulation step.	unsafety $= \Delta S \cdot S \cdot R_b$ Unsafety Density $= \frac{\sum_{S=1}^{S_t}\sum_{V=1}^{V_t} \text{unsafety}_{v,s} \cdot d}{T \cdot L}$ S: Speed of the follower vehicle ΔS: Difference of speed at collision time R_b: unsafe parameter V_t: nb of vehicles in the link S_t: nb of simulation steps within aggregation period d: simulation step duration [s]		Rear-end collisions, lane based traffic		(Mahmud, Md, Hoque, & Tavassoli., 2017)

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		T: aggregation period duration $[s]$ L: section length $[m]$				
Difference of Space distance and Stopping distance (DSS)	DSS is defined by the difference of the space and stopping distance.	$\mathrm{DSS} = \left(\frac{v_1^2}{2\mu g} + d_2\right) - \left(v^2 \Delta t + \frac{v_1^2}{2\mu g}\right)$ S: Space distance (m) Stop: Stop distance (m) v_1 : Velocity of following vehicle (m/s) v_2: Velocity of leading vehicle (m/s) μ : Friction coefficient g: Gravity acceleration (m/s^2) d_2: Distance between leading vehicle and following vehicle (m) Δt: Reaction time	Values < 0 are considered dangerous	Rear-end collisions, turning scenarios		(Mahmud, Md, Hoque, & Tavassoli., 2017)
Time Integrated DSS (TIDSS)	Total value of the time integrated value gap between DSS and the dangerous threshold value.	$TIDSS = \int_0^t \{TH - (DSS)\} dt$ TH is the threshold value		Rear-end collisions		(Mahmud, Md, Hoque, & Tavassoli., 2017)
Deceleration Rate to Avoid the Crash (DRAC)	Differential speed between a following/ response vehicle and its corresponding subject/ lead	$DRAC_{LV,t+1}^{REAR} = \frac{(V_{LV,t} - V_{SV,t})^2}{D}$ Or $DRAC_{LV,t+1}^{REAR} = \frac{(V_{LV,t} - V_{SV,t})^2}{2 \times D}$	AASHTO threshold of 3.40 m/s2 for most drivers.	Rear-end collisions, hit object / parked vehicle, pedestrian. Merging /	Urban, Rural and Highway	

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	vehicle (SV) divided by their closing time.	V_{SV}: Velocity of following venicle $(\mathrm{m/s})$ V_{LV}: Velocity of leading vehicle $(\mathrm{m/s})$ D : Relative Distance	Another study recommend conflict if DRAC exceeds 3.35m/s2.	diverging manoeuvres		
Crash Potential Index (CPI)	Probability that a given vehicle DRAC exceeds its maximum available deceleration rate (MADR) during a given time interval. Driver reaction time can be incorporated in DRAC → modified CPI	$\mathrm{CPI_i} = \frac{\sum_{t=ti_i}^{tf_i} P\left(\mathrm{MADR}^{(a_1,a_2,\ldots,a_n)} \leq \mathrm{DRAC_{i,t}}\right) \cdot \Delta t \cdot b}{\mathrm{T_i}}$ DRAC $_{\mathrm{i,t}}$: Deceleration rate to avoid the crash $(\mathrm{m/s^2})$ MADR $(a_1, a_2, \ldots, a_n)$: Random variable following normal distribution for a given set of traffic and environmental attributes $(\mathrm{a_1, a_2, \ldots, a_n})(\mathrm{m/s^2})$ $\mathrm{ti_i}$: Initial simulated time interval for vehicle i $\mathrm{tf_i}$: Final simulated time interval for vehicle i Δt: Simulation time interval $\mathrm{T_i}$: Total travel time for vehicle i b: A binary state variable, 1 if a vehicle interaction exists and 0 otherwise.	CPI>0 is considered very dangerous	Rear-end collisions, hit object / parked vehicle, pedestrian. Merging / diverging manoeuvres		(Shi, Wong, Li, & Chai, 2018)
Criticality Index Function (CIF)	Multiplication of vehicle speed with the required deceleration	Criticality Index $= \mathrm{V^2/TTC}$ (Time to Conflict) V: Velocity (m/s)		Collision with object	Highway and urban	(Mahmud, Md, Hoque, & Tavassoli., 2017)

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Margin to Collision **(MTC)**	Ratio of the summation of the inter-vehicular distance and the stopping distance of the preceding vehicle divided by the stopping distance the following vehicle.			Collision with object		(Mahmud, Md, Hoque, & Tavassoli., 2017)

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Table 6 Mapping of SMoS for car-PTW Interactions to scenarios

Metric	Definition	Formula	Thresholds	Scenarios	Use Case	Ref
Safety Gap distance	Longitudinal safety gap distance that the motorcyclist has to maintain when senses the leading vehicle decelerating	$\Delta D_n^{\text{unswerving}} = v_n \tau - \frac{v_n^2}{2b_n} + \frac{v_{n-1}^2}{2b_{n-1}},$	Longitudinal gap:7.00m (0.32) for the left half 5.42m (0.34) for the right-half	Congested Urban, car-following/rear-end(avg. speed 36km/h)	Urban	(Lee, Polak, Bell, & Wigan, 2012)
Crash Propensity Metric (CPM) **(not specific for PTWs)**	Crash Propensity Metric (CPM) is the probability of a conflict to become a crash	The sum of Groups A and B-2 can be used as the CPM. $\text{Percentage(Group A)} : P(\text{RT} \geq \text{TTC}) \times 100\%$ $= \left\{1 - \left[\frac{1}{2} + \frac{1}{2}\text{erf}\left(\frac{\ln \text{TTC} - \mu_{\text{rt}}}{\sqrt{2\sigma_{\text{rt}}^2}}\right)\right]\right\} \times 100\%$ For *RT* is the reaction time; $\boldsymbol{\mu_{rt}}$ and $\boldsymbol{\sigma_{rt}}$ are the mean and standard deviation of reaction time distribution which is assumed to be a log-normal distribution; ***erf*** is the error	Low severity: CPM < 0.10 High severity: CPM > 0.90	Urban, car-following/rear-end	Urban	(Wang & Stamatiadis, 2014)

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		function. $\text{Percentage(Group B2)} = P(\text{RT} < \text{TTC}, \text{MABR} < \text{RBR}) \times 100\%$ $= P(\text{RT} < \text{TTC})P(\text{MABR} < \text{RBR} \mid \text{RT} < \text{TTC}) \times 100\%$ $= \int_0^{\text{TTC}} \frac{1}{x\sqrt{2\pi\sigma_{\text{rt}}^2}} e^{-\frac{(\ln x - \mu_{\text{rt}})^2}{2\sigma_{\text{rt}}^2}} \cdot \frac{\phi\left(\frac{y-\mu_{\text{MABR}}}{\sigma_{\text{MABR}}}\right) - \phi\left(\frac{L_{\text{MABR}}-\mu_{\text{MABR}}}{\sigma_{\text{MABR}}}\right)}{\phi\left(\frac{U_{\text{MABR}}-\mu_{\text{MABR}}}{\sigma_{\text{MABR}}}\right) - \phi\left(\frac{L_{\text{MABR}}-\mu_{\text{MABR}}}{\sigma_{\text{MABR}}}\right)} dx \times 100\%$ ***RT*** is the reaction time; ***MABR*** is the maximum braking rate; $\boldsymbol{\mu_{rt}}$ and $\boldsymbol{\sigma_{rt}}$ are the mean and standard deviation of reaction time distribution which is assumed to be a log–normal distribution; $\boldsymbol{\mu_{MABR}}$ and $\boldsymbol{\sigma_{MABR}}$ are the mean and standard deviation of *MABR* distribution which is assumed to be a truncated normal distribution; $\boldsymbol{L_{MABR}}$ and $\boldsymbol{U_{MABR}}$ are the lower and the upper limit of MABR; ***x*** is the reaction time of a driver; ***y*** is the required braking rate (*RBR*) for the driver; ***ϕ(·)*** is the cumulative distribution function of the standard normal distribution.				

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VRU Literature Survey

This structured literature review (Figure 4) was conducted between August and November 2020 to identify relevant parameters to differentiate (non-)safety critical driving situations of VRUs in traffic situations (Studies from 2002 to 2020). The keywords *VRUs, pedestrian, cyclist, crash data, VR, simulation, experiment, perception, attitude, intersection, roundabout,* and *indicator* were used in the platforms *Semantic scholar, Google scholar, Researchgate* and *Umlibrary* to get an overview of relevant studies. *Recent, peer-reviewed, studies* with the *perspective of VRUs'* and a *general high quality of the publication* served as selection criteria.

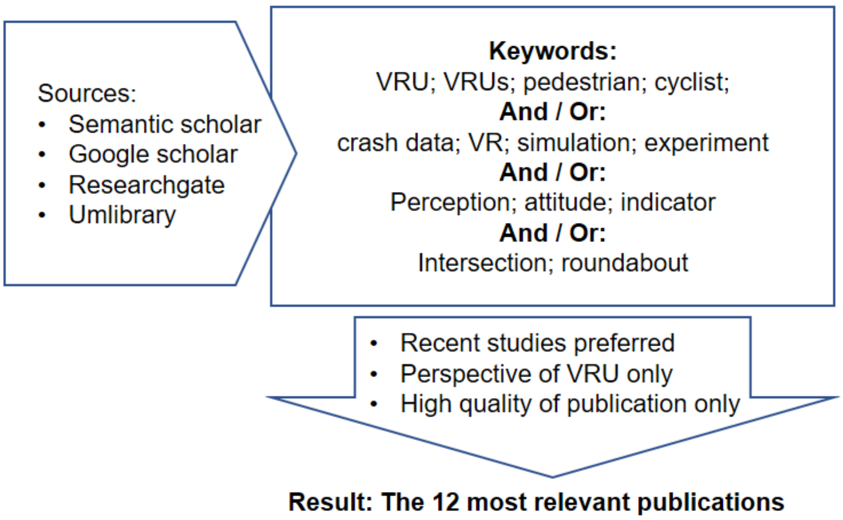

Figure 4: Procedure of Literature Review

Study 1 (pedestrians, (Oron-Gilad & Meir, 2020)): In a simulator study, *N* = 46 participants were asked to decide when to cross a road in three traffic situations (T-junction, traffic circle, pedestrian crossing) and to indicate their decision via pressing a button. Response sensitivity, response time, and qualitative reasoning were assessed. Hazard perception skills and adequate perception indicator measures, like *age* or *complexity of situation* were revealed through logistic regressions and qualitative assessment. Conclusion: Participants based their decisions on the road most salient features like vehicles and the presence of another pedestrian.

Study 2 (pedestrians and cyclists, (Habibovic & Davidsson, 2012)): In a crash data analysis, *N* = 56 crashes (VRU-car incidents) were analysed regarding weather and light conditions as well as intersection type. Based on timing and directions of the VRUs the analysis revealed that 70% of the VRUs saw the conflicting car before the collision, but still misunderstood the traffic situation and/or made an inadequate plan of action. Conclusion: The mere possibility of seeing a hazard can therefore not account for reacting adequately and further research is needed on why crash participants react inadequate in a traffic situation.

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Study 3 (pedestrians, (Tabibi & Pfeffer, 2003)): In a reaction experiment, N = 128 participants were asked to identify safe and dangerous road crossings based on a computer presentation with and without safety-relevant information displayed. The ability to identify objectively safe and dangerous road-crossing sites and attention level were assessed. Significantly longer identification times were needed in condition with irrelevant information, while limited sights produced more errors. This leads to the conclusion that the *quality* and *quantity* of *cues for adequate behaviour* are both relevant for pedestrians, when they encounter complex traffic situations. The central element for a decision of the participants is their subjective evaluation based on the presented cues.

Study 4 (pedestrians, (Guéguen, Meineri, & Eyssartier, 2015)): In a field experiment at four pedestrian crossings, the stopping behaviour of N = 2560 cars was assessed, when four different confederates were staring at the oncoming vehicles. It was concluded that controlled actions by a pedestrian, like *staring* at a vehicle, have an impact on the possibility of the vehicle to stop for the passenger.

Study 5 (cyclists, (Liu, et al., 2012)): In a simulator study, N = 60 participants were asked to respond to right-turning motorised vehicles. Steering and braking behaviour was assessed based on three safety-critical behaviours of motorised vehicles and three cut-in time gaps. Five different patterns of reactions were identified: 1) early response and quickly depress the brake; 2) last-moment response and slowly depress the brake; 3) late response quickly depress the brake; 4) very late response; and 5) quickly depress the brake, and no response. These patterns provide evidence that the estimated behaviour of a cyclist cannot be predicted reliably based on simple probability calculation containing connections between seeing a hazard, identifying it as a risk, and reacting adequately.

Study 6 (cyclists, (Dozza & Werneke, 2014)): In a naturalistic bicycle driving study, N = 16 participants were asked to press a button, when they encountered a critical event. Additionally, a critical event was assessed, when a kinematic trigger reached a threshold. Based on a subjective and objective critical events analysis, odds ratios calculations revealed three main risks for encountering a critical traffic situation, when driving a bicycle in an urban area: *intersections* (4x to 12x increased risk), *poor road maintenance* (10x increased risk) and *crossing VRUs* (2x increased risk). Conclusion: The three main risks for encountering critical traffic situations in urban area on a bicycle as identified in the study could be assessed via the combination of objective and subjective data.

Study 7 (cyclists, (Abadi M. G., Hurwitz, Sheth, McCormack, & Goodchild, 2019)): In a simulator study, N = 48 participants encountered a potential critical traffic situation including a bicycle lane and a commercial vehicle loading zone. Velocity, lateral position, and crash events of the participants were assessed based on three markings in the conflict zone, three levels of truck manoeuvres, and two levels of traffic signs. It was observed that the presence of a truck or warning sign influenced the velocity and lateral position. The results indicate furthermore that infrastructural layout and therefore cues for adequate and desired behaviour in a traffic situation might be central for a risk reducing behaviour, such as reducing the speed or an adaptation of the lateral lane position.

Study 8 (cyclists, (Kovácsová, de Winter, & Hagenzieker, 2019)): Within a video-based online survey, the anticipatory behaviour of N = 1384 cyclists from 65 countries was assessed during

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safety-critical situations. Freezing moments and criticality of the traffic situations of the 50 experimental video clips were modified to assess self-reported slowing down behaviour and subjective prediction of the behaviour of the conflicting cars displayed in the videos. The results indicate that high level of perceived risk is a significant predictor of slowing-down behaviour. Conclusion: The subjectively perceived risk is influenced by the traffic situations criticality and should be a core for modelling cyclists' behaviour.

Study 9 (cyclists, (Doorley, et al., 2015)): In a quasi-experimental/partially controlled field study *N* = 8 participants covered two routes and were asked to give a risk rating at 24 points in time. Additionally, heart rate was assessed. Results indicate a significant dependency between perceptions of risk among cyclists and heart rate. Conclusion: *Heart rate* can be used as a non-intrusive way to estimate risk perception of cyclists.

Study 10 (cyclists, (Abadi, Hurwitz, & Macuga, 2019)): In an online study, *N* = 342 participants were asked to express their most probable reaction given a risky situation. Distracted cycling, subjective norms, habits, and safety beliefs were assessed. Results indicate that *perceived level of comfort* (PLOC) together with *incidents in the past,* and the general *safety beliefs* of the participant are the central elements in a structural equation model, which predicts a safe or risky response to a potential hazard. Conclusion: The subjective appreciation (comfort) of the traffic situation seems to be essential for predicting the behaviour of cyclists.

Study 11 (cyclists, (Alvergren, Karlsson, Wallgren, Op de Camp, & Nabvii Niavi, 2019)): In the EU-project MeBeSafe the behaviour of *N* = 93 cyclists was assessed in a quasi-experiment based on visual nudges. Two variants of digital signs and four markings on the bicycle lane were applied, while trajectories, speeds, braking distances, and head movement of the passing cyclists were assessed objectively. Additionally, the nudges were rated by questionnaires subjectively. Results revealed significant changes towards desired trajectories and lower speeds at all nudges in comparison to a baseline without nudges. Conclusion: The implemented infrastructural measures can objectively nudge the participants into a desired behaviour.

Study 12 (cars, (Dittrich, 2020)): In a dissertation five empirical studies were carried out as part of the human-centered design process. Key is the first study, where *N* = 34 participants reported their emotions and their triggers while they were driving. Results and the literature examined in this dissertation revealed a positive relation between frustration-inducing traffic situations, subjective reported frustration levels and aggressive driving behaviour. Conclusion: The resulting driving behaviour is not only determined by the situation and its participants, but by the recent experiences and frustration levels of the drivers.

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