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SURVEY

Surrogate Safety Measures: Review and Assessment in Real-World Mixed Traditional and Autonomous Vehicle Platoons

TANMAY DAS[1], M. SHOAIB SAMANDAR[2], MEAGAN KITTLE AUTRY[1], AND NAGUI M. ROUPHAIL[1]
[1]Civil Construction and Environmental Engineering, North Carolina State University, Raleigh, NC 27695, USA
[2]Institute for Transportation Research and Education, Raleigh, NC 27606, USA

Corresponding author: Tanmay Das (tdas@ncsu.edu)

ABSTRACT Surrogate safety measures (SSMs) are critical tools for evaluating the safety performance of mixed traffic. Crashes are rare events, and historical crash data are scarce for mixed traffic that includes autonomous and/ or connected vehicles. Recent safety review papers focus on traditional human-driven vehicles (TVs) and do not encompass advanced technology vehicles such as autonomous vehicles (AVs), connected vehicles (CVs), and connected-autonomous vehicles (CAVs). This study examines the development, implementation, and shortcomings of SSMs and SSM-based models used for mixed traffic safety evaluation. We review the current relevant literature and apply a case study analysis using a real-world mixed traffic dataset. The study summarizes the fundamental SSM guiding concepts, as well as their most significant metrics including threshold values employed in the past for SSMs and SSM-based models. Primary benefits and limitations of examined SSMs and SSM-based models are also underlined. This review reveals significant gaps in the literature that might guide future research paths in SSM-based mixed traffic safety assessment. Critical gaps include the absence of robust SSM threshold selection criteria, the suitability of current SSMs in mixed traffic research, microsimulation modeling that lacks proper calibration and validation, and the absence of a framework for selecting or combining multiple SSMs.

INDEX TERMS Mixed traffic, surrogate safety measures, real-world mixed traffic dataset, autonomous vehicles, connected vehicles, connected-autonomous vehicles.

I. INTRODUCTION

The introduction of autonomous vehicles (AVs) is expected to improve traffic safety by reducing human involvement and driver errors. We define a mixed-traffic condition where the traffic stream contains different vehicle technologies, including connected-autonomous vehicles (CAVs), autonomous vehicles (AVs), connected vehicles (CV), and traditional vehicles (TVs). The traffic dynamics of CAVs and AVs are different from TVs [1]. Therefore, the introduction and mix of these vehicles are likely to impact traffic flow and associated traffic safety.

Most studies on the safety assessment of AVs or CAVs operating in mixed traffic have used traffic conflict concepts due to the absence of historical crash data. A traffic conflict is defined as an observable evasive action taken by a driver to avoid a crash between his/her and neighboring vehicles [2]. Like crashes, traffic conflicts are affected by traffic patterns, road users, road geometry, and other factors. In addition, a relationship exists between crash and traffic conflict frequencies [3]. According to Hyden, most traffic interactions between vehicle pairs are undisturbed passages [3]. A small portion of the interactions can be categorized as potential conflicts, while crashes are sporadic. Assuming the relation between conflicts and crashes is known, it is theoretically possible to estimate the frequency of crashes based on the traffic conflict measurement [4]. Nonetheless, the portion of traffic conflicts that may result in crashes is not fixed; instead, it varies with different traffic compositions and across sites [5].

To measure traffic conflicts, researchers commonly use surrogate safety measures (SSMs). SSMs use pair-wise

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vehicular velocity and spacing attributes derived from vehicular trajectories to report traffic conflicts [6]. The primary goal of using SSMs is to identify probable conflict types emerging from the temporal or spatial proximity of vehicle pairs based on the premise that the closer vehicles are to each other, the more likely they are to collide [7]. However, not all surrogate measures related to traffic safety can be effective SSMs. An effective SSM must be derived from those traffic conflicts potentially linked to crashes [8]. Moreover, there should be a statistically significant relationship between traffic conflicts and the resulting crashes.

Several review papers have shown the importance and applicability of SSMs for the safety assessment of TV traffic streams. For example, Gettman & Head focused their review on SSMs used in simulation [9]. Another review by Mahmud et al. examined proximal SSMs, primarily those that detect traffic conflicts based on temporal or spatial proximity [7]. Johnsson et al. highlighted the SSMs used to assess the safety of vulnerable road users such as pedestrians and bicyclists [10]. SSMs and related traffic conflict approaches were mapped by Arun et al. [11]. Their main goal was to develop a consistent framework for traffic conflict reporting methodologies to use in traffic safety assessments. Arun et al. [12] conducted another review of SSMs, this time focusing on the application of SSMs used for traffic conflict assessment in the period from 2010 to 2019. Zheng et al. conducted a review focusing on the modeling methodologies of traffic conflict frequency and severity [13]. Pinnow et al. discussed the kinematic SSMs, as well as whether these surrogates may be contextualized at different road geometries [14]. Wang et al. reviewed the applications of SSMs in CAV traffic stream safety modeling [15]. Tafidis et al. reviewed the potential safety implications of SAE Level [16] 4 and 5 AVs [17].

Despite the prevalence of SSMs in the safety literature, a comprehensive review of SSMs in the context of mixed traffic safety assessment is missing. In the coming decades, the market share of AVs [16] driving alongside TVs is expected to increase [18], [19]. In addition, since mixed traffic vehicle dynamics are quite different from homogenous traffic streams, a review of the applications of SSMs for mixed traffic safety assessment is an important step for future research in this emerging area.

The objectives of this review paper are (a) to present a comprehensive review of SSMs used in mixed traffic safety assessment; (b) highlight their applications; and (c) uncover research gaps. In addition, the study applies SSMs to a dataset of mixed AVs and TVs to highlight their utility and levels of consistency in mixed traffic safety evaluation. The paper is organized as follows: First, we describe the method used to identify and review the relevant literature and explain the case study. Next, we present the findings, organized by individual SSMs and SSM-based models. Finally, a discussion and recommendations for future research are presented, followed by conclusions.

II. METHODOLOGY

In this section, we describe the method used to search and review the current literature on the use of SSMs for mixed traffic safety. We then provide a case study description and application of the method to a real-world dataset.

A. LITERATURE REVIEW PROCESS

The authors adopted a narrative review following the format described by Wee & Banister to guide the literature search [20]. **Figure 1** shows the workflow followed to identify and screen articles for eligibility. First, we identified keywords for the search. Several synonyms were used for traffic conflicts, such as near-crash, safety-critical events, near misses, and risky events. In some studies, traffic conflict measurements are themselves referred to as surrogate measures. In other studies, the term surrogate measures stand for conflict indicators. Vehicular proximity in time and space is also used synonymously with surrogate measures. As this review focuses on mixed traffic comprising CAVs, AVs, CVs, and TVs, synonyms of those terms were also used. Thus, the following keywords and their combinations were used to search the literature: traffic conflicts, safety surrogate, surrogate measures, near-crash, near miss, mixed traffic near-crash, connected automated vehicle, automated vehicle, connected vehicle, and safety simulation. The search focused on the following databases: Google Scholar, Web of Science, Scopus, Transport Research International Documentation (TRID), and Taylor & Francis.

We used a direct Google search for essential reports or manuals, such as the United States' Federal Highway Administration (FHWA) Surrogate Safety Assessment Model [21]. Our search approach is not intended to be exhaustive; rather, it is to search for those relevant studies that properly address the research objectives. Selected sources included peer-reviewed journal articles and conference proceedings. In addition, some textbooks, reports, doctoral dissertations, masters' theses, and unpublished working papers that significantly contribute to surrogate safety measure research were also included. In several cases, a backward snowballing strategy [22] was used to identify relevant literature on the subject. Because the notion of surrogate safety measures in mixed traffic is still in its development, the backward snowballing method allowed us to collect and review relevant material that was deemed appropriate. In total, this search strategy yielded 160 studies that have used SSMs to assess traffic safety. Among these, only 48 studies focused on mixed traffic safety. We used RefWorks, a reference management tool, to manage the references.

B. CASE STUDY DESCRIPTION

Scholars have adopted models of adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) controllers to assess the impact of AVs and CAVs on traffic safety and operation [23], [24]. The main difference between ACC and CACC is that the latter has the vehicle to

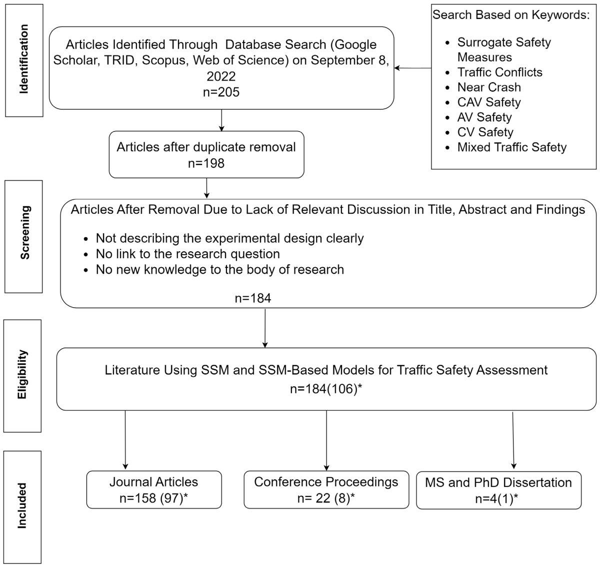


FIGURE 1. Literature search approach.

TABLE 1. Case study platooning scenarios.

Leader		Follower		AVs Automation Level (SAE, 2018)	Total Experiment Time (s) and Distance (m)
Vehicle Type	Model	Vehicle Type	Model		
TV	Hyundai Ioniq hybrid 2019	TV	Kia Niro 2019	N/A	374.40 s 11,075 m
AV	Mitsubishi SpaceStar 2019	AV	Ford S Max 2019	Level 2	734.80 s 22,401 m
TV	Hyundai Ioniq hybrid 2019	AV	Ford S Max 2019	Level 2	734.80 s 22,421 m
AV	Mitsubishi SpaceStar 2019	TV	Kia Niro 2019	Level 2	734.80 s 22,417 m

everything (V2X) including vehicle-to-infrastructure (V2I) and/or vehicle-to-vehicle (V2V) connectivity.

Though the market share of ACC-equipped vehicles has increased, virtually no private or commercial CACC-equipped vehicles currently drive on the road. A few CACC prototypes are used in controlled environments for testing purposes only [25]. ACC-equipped vehicles are considered the first proxy of future AVs [26], therefore, researchers' interest in assessing ACC vehicles' impact on traffic safety has also increased. In this case study, we use the OpenACC [27] dataset. It contains several experimental car-following trajectory data collected in different campaigns using test tracks and actual highways, thus providing an overview of AV dynamics that use ACC as their car-following algorithm under various driving conditions. This study uses a dataset collected in the first quarter of 2019 at a site in northern Italy.

The OpenACC campaign involved three days of car-following testing from Ispra to Vicolungo and back. Testing was performed with various vehicle brands and models driving in car-platoon formations [27]. The campaign was on-road, and all vehicles were equipped with Ublox 8 GNSS data acquisition devices. The acquired data had a sampling frequency of 10 Hz [27]. The vehicles, while driving in AV mode, used ACC car-following. When in ACC mode, human drivers did not intervene. Thus, the vehicles' acceleration and deceleration were strictly guided by the ACC function. In emergency cases, drivers were allowed to apply the brake pedal. AVs were programmed to use the shortest time gap setting to avoid cut-in situations from other users. Additionally, no overtaking was performed. For this study, we selected four different leader-follower car-following scenarios as shown in **Table 1**: (a) TV-TV platoon: (b) AV-AV platoon (c) a TV-AV platoon and (d) AV-TV platoon.

We extracted, for each vehicle in a platoon, the following attributes:

1. Speed profile
2. Time gap distribution with other vehicles
3. Acceleration profile
4. Relative speed vs. lead vehicle
5. Relative distance vs. lead vehicle
6. Inter-vehicular spacing

The extracted data was used for SSM analysis. All scenarios were carried out in the open highway with no interruptions.

III. FINDINGS

In this section, we present a summary of the findings based on the literature review and case study analysis. We describe the applications of SSMs, as well as their shortcomings in the context of mixed traffic safety evaluation.

A. SSMs USED IN MIXED TRAFFIC SAFETY RESEARCH

We first categorize SSMs used in mixed traffic safety assessment into two classes a) Individual SSMs and b) SSM-based models. We further divide the individual SSMs into five categories and the SSM-based models into six categories. In this section, we discuss the applications and limitations of the individual SSMs and SSM-based models' for assessing mixed traffic safety. Definitions and related equations for individual SSMs can be found elsewhere (**Appendix found within the supplementary files on IEEE Xplore**). A literature summary of SSM applications in mixed traffic safety assessment is given in the **Appendix found within the supplementary files on IEEE Xplore**.

1) INDIVIDUAL SSMs

a: TIME-BASED SSMS (TSSMS)

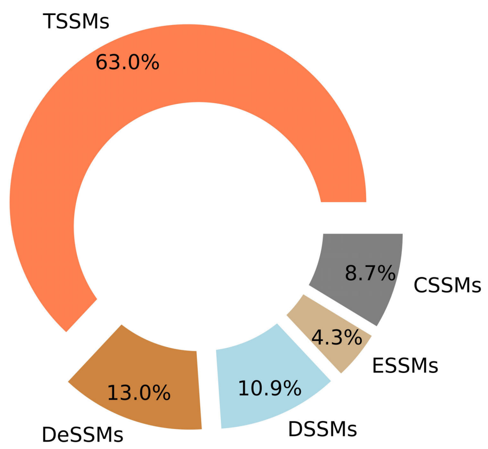
TSSMs are the most frequently used SSM for mixed traffic safety assessment as depicted in **Figure 2**. They use the temporal proximity between a vehicle pair to flag a traffic interaction as traffic conflict [28]. TSSMs assume that vehicle pairs may be on a collision course within a considered time interval [7]. Therefore, TSSMs cannot identify conflicts where a collision course between vehicle pairs does not exist [29]. Time to collision (TTC) is the most widely used TSSM for mixed traffic safety assessment. TTC is popular because of its simplicity in measurement; however, TTC has several limitations. First, TTC can only report the number of conflicts, but it cannot assess the severity of conflicts [30]. Second, TTC assumes that consecutive vehicles will maintain current speeds while ignoring many potential conflicts due to acceleration or deceleration discrepancies [31]. Third, TTC cannot measure the potential risk of car-following scenarios when the following vehicle's speed is equal or slightly below that of the leading vehicle, while the spacing between two vehicles is comparatively short, so that a slight perturbation could generate a rear-end collision risk [32].

In addition, TTC is strictly dependent on linear measurements. Thus, for turning movements, TTC may not provide the correct interpretation. The first limitation of TTC is addressed by several other TSSMs. For example, the time-integrated time-to-collision (TIT), a TTC-dependent SSM introduced by Minderhoud & Bovy [33] accounts for the severity of traffic conflicts by integrating the difference between a TTC threshold and the TTC value at time instant t. Ozbay et al. [34] proposed a modified time to collision (MTTC) to overcome the shortcomings related to acceleration or deceleration discrepancies. The third limitation is addressed in the time to collision with disturbance (TTCD) SSM introduced by Xie et al. [35]. TTCD can assess rear-end conflicts when the following vehicle is slower than the leading vehicle and the leading vehicle generates a disturbance to the following vehicle by an abrupt deceleration. Another widely used TSSM used for mixed traffic safety assessment is post encroachment time (PET). PET is used for angle and turning traffic conflict reporting. Several drawbacks are noted for conflict reporting using PET. First, though a lower PET value indicates a higher conflict severity, it does not consider the vehicle pairs' speed and distance. Thus, the severity results may not be accurate. Second, PET measurement requires a fixed spatial collision point, and thus it cannot consider conflicts that change its spatial dynamics, especially in rear-end interactions. Finally, PET is not suitable for conflict identification while the vehicle pairs are in the same lane.

b: DECELERATION-BASED SSMS (DESSMS)

In car-following situations, the following vehicle will decelerate in response to the leading vehicle's evasive action to avoid a collision [7]. DeSSMs evolved from the idea that traffic conflicts can be reported by the rate of deceleration applied in response to a sudden event. Like TSSMs, DeSSMs presume that the vehicle pairs must have a collision course and unchanged path and speed within the considered time interval. In addition, DeSSMs must have a threshold to differentiate between conflicting and non-conflicting traffic interactions [9].

Deceleration rate to avoid crash (DRAC) is the most frequently used deceleration-based SSM for mixed traffic safety assessment, as shown in the **Appendix found within the supplementary files on IEEE Xplore**. Our review found that DRAC does not consider the response time (RT) of the following vehicle. Adomah et al. suggest a modified DRAC



TSSMs	Time-based SSMs	DSSMs	Distance-based SSMs
DeSSMs	Deceleration-based SSMs	ESSMs	Energy-based SSMs
CSSMs	Combined SSMs		

FIGURE 2. Frequency of SSM categories documented in the literature.

(MDRAC) as an improvement over regular DRAC [36]. The key distinction between DRAC and MDRAC is that the latter considers the response time of the following vehicle. In addition, DRAC cannot account for several potential traffic conflicts since it does not consider road and vehicle types [6]. For example, the same DRAC threshold is used under both dry and wet pavement conditions. Furthermore, heavy vehicles have a more difficult braking maneuver due to their greater mass [37]. Therefore, using the same DRAC threshold for both passenger cars and heavy vehicles is inadvisable.

To overcome some of these limitations, Cunto & Saccomanno [6] proposed a crash potential index (CPI) that estimates individual vehicle crash risks considering pavement conditions and driver type. CPI gives the probability of a given vehicle's DRAC exceeding its maximum allowable deceleration rate (MADR) during a given interval. MADR is defined as the maximum deceleration a vehicle can apply to avoid a collision for a given road and vehicle type. CPI works well with rear end collision detection; however, it is not suitable for detecting conflicts due to lateral movements [7]. Jo et al. [38] and Ko et al. [39] used CPI to assess mixed traffic safety comprising CVs and TVs. However, no documented application of CPI in mixed AVs or CAVs was found in the documented literature. According to Cunto & Saccomanno [6], the mean and standard deviation of MADR for passenger vehicles are 8.45 m/s^2 and 1.40 m/s^2, respectively. For both trucks and buses, the mean and standard deviation of MADR is 5.01 m/s^2 and 1.40 m/s^2, respectively. We expect that in the application of CPI to mixed AVs and CAVs fleets, significant changes to the values of MADR will be needed to reflect change in response patterns. This is a ripe area for future research.

c: DISTANCE-BASED SSMS (DSSMS)

Here, the distance available to avoid a collision is the main element for conflict reporting. DSSMs depend on the vehicles' safe stopping distance (SSD) computation. SSD measures the distance within which the following vehicle could maneuver to avoid a collision with the leading vehicle with maximum deceleration when the leading vehicle makes a sudden deceleration. SSD depends on the RT of the vehicles, initial speed, and pavement condition. One advantage of using DSSMs is that the threshold is mostly fixed. However, RT estimates are critical to producing accurate outcomes in DSSMs traffic conflict reporting. Researchers have used different values of RT for different classes of vehicles. For example, Li et al. [40] assumed 0.1 s RT for CAVs, and Okamura et al. [41] assumed 0.3 s RT for AVs. Neither author justified their RT values. Should the assumption of RT be inaccurate, then the DSSMs may under or over report the number of conflicts.

In this review, we found that time-exposed rear end crash risk (TERCRI) [42] is the most frequently cited DSSM (**Appendix found within the supplementary files on IEEE Xplore**). TERCRI uses the concept of rear-end crash risk index (RCRI). RCRI is also used for mixed CAVs and TVs, such as in Li et al. [40]. Our review also found that DSSMs cannot report traffic conflicts due to lane changes. In addition, DSSMs do not consider overtaking sight distance, which could be a critical safety issue for two-way traffic.

d: ENERGY-BASED SSMS (ESSMS)

The idea of ESSMs is borrowed from vehicle kinetics, which describes the influence of speed on kinetic energy involved in collisions. ESSMs measure the amount of energy dissipated during a collision. The dissipated energy in a collision depends on the speeds and the mass of vehicle pairs involved and the angle at which the vehicles approach each other (see [43]). The primary assumption in ESSMs is that all traffic collisions are inelastic. Therefore, the amount of energy dissipated mirrors the conflict severity. In addition, no threshold is used for ESSMs to report a traffic conflict; instead, it only reports the traffic conflict severity. One of the main limitations of ESSM resides within its assumption that all collisions are inelastic; therefore, ESSMs cannot measure the energy absorbed by the deformation of the colliding bodies.

The only documented ESSM used for mixed traffic safety assessment is DeltaV. DeltaV shows the change in velocity between pre-collision and post-collision trajectories of a vehicle pair (See **Appendix found within the supplementary files on IEEE Xplore**). The surrogate safety assessment model (SSAM) reports DeltaV as a part of its output. However, the implications of DeltaV are limited because it does not consider the temporal or spatial proximity of a traffic conflict. In the SSAM model, DeltaV is measured between two vehicles considering the angle and velocity they have when TTC_{min} takes place. Therefore, an encounter with a TTC_{min} greater than a second can have the same computed DeltaV value as an encounter with a TTC_{min} of less than a second. This is highly in dispute with the principles of TSSMs.

e: COMBINED SSMS (CSSMS)

SSMs that do not fit into any of the preceding distinctive classes and are either combination of previous distinctive classes or use new a knowledge domain are referred to as combined SSMs. Combined SSMs have been developed to overcome the constraints of single class SSMs by providing additional aspects and by adding new knowledge to interpreting traffic conflicts. Driving volatility (DV) is frequently used in mixed traffic safety assessment (see **Appendix found within the supplementary files on IEEE Xplore**). DV uses vehicle kinematics and statistics knowledge to report a traffic conflict by tracking miniscule variations (e.g., speed, acceleration) in driving that affect the vehicle's longitudinal control. Increases in DV indicate an increase in collision probability [44]. Deviation in speed, acceleration, and jerk can be attributed as DV [45], [46](See **Appendix found within the supplementary files on IEEE Xplore**). Ding et al. [47] introduced an average damping ratio (ADR) to show how vehicular oscillations are damped or amplified through a vehicle platoon. Vehicular oscillations may be the main cause of system string instability. Conversely, string stability describes how a vehicle string mitigates the oscillation. Therefore, if the oscillation is damped as it propagates back through the platoon, the collision probability is reduced and vice-versa. ADR uses the combined knowledge domain of vehicle kinematics and statistics to show string stability as a surrogate to report rear- end conflicts [48]. Finally, MaxS (maximum speed of the vehicle), a default output of the SSAM model, is used by Tibljaš et al. [49] to assess the safety impact of AVs in mixed traffic at a roundabout.

2) SAFETY MODELS

Surrogate safety models report traffic conflicts by combining separate SSMs or by using data-driven probabilistic estimation methods. To the authors' best knowledge, six categories of surrogate safety models have been used for mixed traffic safety assessment: 1) Uncertainty model; 2) Extreme value theory model; 3) Causal and counterfactual Model; and 4) SSAM; 5) Deep learning (DL) and machine learning (ML) based surrogate safety models; and 6) Fuzzy logic based surrogate safety model.

a: UNCERTAINTY MODEL

Vehicle motion parameter estimates (e.g., speed, acceleration or deceleration, time gap) are significant aspects to consider when reporting traffic conflicts, but so are variations in vehicle types, driving behavior, and road geometry. Different combinations of drivers and vehicles could produce different results for the same vehicular motion characteristics. According to Davis et al. [50], an accurate model that estimates traffic conflicts may be built by considering the uncertainty in driving behavior and vehicles while evaluating the crash probability.

Uncertainty modeling aims to build a probabilistic model using available data to represent both the marginal and joint probability density function (PDF) of the random variables in the crash prediction system. Uncertainties in variations in vehicles, driving behavior, and road geometry are considered random variables in the uncertainty model. The general equation for the uncertainty models' crash prediction is described as follows:

$$P\,(crash) = 1 - \sum_{i=0}^{N} P(A_i) \tag{1}$$

where A_i represents the i^{th} necessary measure for crash avoidance. These measures include but are not limited to steering rate, braking rate, and road geometry. The measures can be mutually exclusive or correlated. For probability estimation, the sample distribution must be identified. Two methods estimate the PDF of random variables based on data: a) a parametric approach, which fits the data to a specific probability distribution, such as negative binomial, exponential or Gaussian distributions; and b) a nonparametric approach. The latter represents any arbitrary distribution shape entirely based on available data using kernel functions or mixture models (e.g., Gaussian mixture model (GMM) and copula functions). For example, Liu et al. [51] used a Gaussian copula model in the uncertainty modeling step to accurately represent various uncertainty sources in the road traffic conditions based on real-world AV data.

b: EXTREME VALUE THEORY (EVT)

Extreme value analysis can model the stochastic behavior of the process that is abnormally large or small within a dataset found in the tails of probability distributions. The EVT approach in safety analysis is used because it can estimate those rare, unsafe traffic interactions or traffic conflicts [52]. EVT makes the implicit assumption that the stochastic behavior of the modeled process is sufficiently smooth to allow extrapolation to unobserved levels [53]. Therefore, EVT aims to predict probabilities for rare events such as a crash. EVT offers two methods to sample extreme events: a) The block maxima (BM) using generalized extreme value distribution (GEV), and b) the peak over threshold (POT) using generalized pareto distribution (GPD). The BM method divides the sample time into blocks of a certain length and samples the largest value (or r largest values) in each block. In contrast, in the POT method, all peak values are sampled, and the values over a certain threshold are used to model the extremes. Åsljung et al. [54] applied EVT to estimate AV safety. The authors used the POT method to define the probability distribution.

c: CAUSAL AND COUNTERFACTUAL MODEL

According to the causal model, the probability of an encounter yielding a traffic conflict depends on the initial condition (U) and evasive action (X), where the probability of a crash is:

$$P\,(y, x, u) = P\,(y \mid x, u)\,P\,(x \mid u)\,P(u) \tag{2}$$

Here, y is crash-related outcome and $P\,(y, x, u)$ is the probability distribution of the crash-related outcome. $P(u)$ is a probability distribution over the values taken on the initial conditions; $P(x|u)$ is a conditional probability distribution for the evasive action; and $P(y|x, u)$ is a conditional probability distribution for the evasive action and the initial variables. Once the traffic probabilities for each of a set of evasive events and initial conditions are calculated, the expected number of traffic conflicts corresponding to the observed conflicts can be obtained by summing the probabilities [50]. Tarko and Lizarazo [5] demonstrated the use of causal relationship in their study estimating rear end conflicts using driving simulator data. The authors assumed that a traffic interaction could be a conflict if caused by a failure or lag in the response of road users. Therefore, using the failure or lag in response as a cause, the authors estimated the probability of rear end crashes.

d: SURROGATE SAFETY ASSESSMENT MODEL (SSAM)

SSAM combines multiple independent SSMs into a model to report a traffic conflict. It is a software that extracts vehicle trajectory information from microscopic models to automatically find, classify, and analyze traffic conflicts [21]. SSAM also has statistical analysis features for conflict frequency and severity reporting. A facility simulated with the desired traffic conditions employs SSAM to assess traffic safety (typically simulating several replications with different random number seeds). Each simulation run generates a TRJ file containing the associated vehicular trajectories. SSAM serves as a post-processor to evaluate the batch of TRJ files. It looks for conflict scenarios in vehicle-to-vehicle encounters, collects, and reports them all.

e: DEEP LEARNING (DL) AND MACHINE LEARNING (ML) BASED SURROGATE SAFETY MODELS

Deep and machine learning methods have been widely reported due to the availability of computational resources and the emergence of extensive data generated from multiple sources [55]. These high-frequency naturalistic driving data contain detailed information on crashes and near-crash events. DL and ML-based surrogate models use this information coupled with driver behavior and vehicular movements to report a traffic conflict in real-time [56]. Our review found abundant applications of ML-based road safety models for homogenous traffic streams (TV, AV, or CV). Some popular ML techniques used for road safety research include regression analysis [57], decision trees [58], and support vector machines (SVMs) [59]. Similarly, the application of DL-based surrogate safety models for homogenous traffic streams (TV, AV, or CV) is plentiful [60], [61], [62], [63], [64], [65]. For example, Hu et al. used individual SSMs and machine learning models for initial prediction of traffic conflicts and coupled the outcomes with macro traffic state of TV stream to propose a deep leaning based surrogate safety model [65]. Using a different approach, Jiang et al. combined a convolutional neural network (CNN) and a long short-term memory

(LSTM) based neural network to report traffic conflicts. The authors used CNN to extract trajectory data from traffic videos and LSTM to predict traffic conflicts. Our review found that the application of deep learning method to report traffic conflicts considering mixed traffic is insufficient [66], [67]. In one of just two existing studies, Arvin et al. used CNN-LSTM to report traffic conflicts considering mixed AV-TV traffic [67].

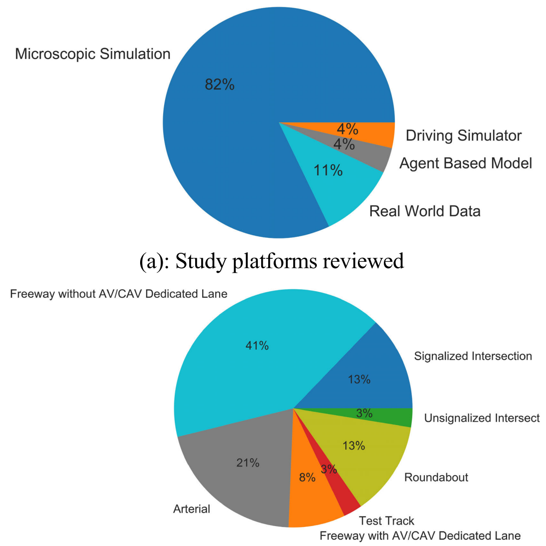
f: FUZZY LOGIC-BASED SURROGATE SAFETY MODELS

Fuzzy logic-based models are not constrained to binary cases of true and false; rather, fuzzy logic includes 0 and 1 as extreme cases of truth but with various intermediate degrees of truth [68]. Also, most of the SSMs employed rely on classical set theory to separate safe and unsafe conditions, using thresholds that are many times arbitrary. However, considering much of the data used, the recognition and response lag of the controllers, driver heterogeneity, manufacturer heterogeneity, and the consideration of marginal error, it is reasonable to assume that a definite distinction between totally safe and entirely unsafe conditions is difficult [69]. Therefore, researchers have used fuzzy-based SSM to avoid rigid thresholds and consider system uncertainties [68], [69], [70], [71]. Among the studies of this topic, Mattas et al. used real-world AV trajectory data to validate the proposed fuzzy logic based SSM [70]. The authors found that the fuzzy-based SSM outperformed traditional SSMs in reporting traffic conflicts. The fuzzy logic based reported traffic conflicts yielded a higher correlation with actual safety-critical situations than the traditional SSM-reported traffic conflicts.

B. STUDY PLATFORMS AND FACILITIES COVERED

Among the literature that dealt with mixed traffic safety assessment, microsimulation studies were prevalent (82%) per **Figure 3(a)**. Only 11% of the studies used real-world data, and only a handful were in driving simulators (4%) or agent-based modeling (4%). Among the simulation studies, 34 (89%) out of 38 studies used TTC as an SSM. Real-world studies also used TTC. The type of study platform heavily influenced the choice of SSMs in real-world studies. For example, studies that used real-world data in mixed traffic collected their data on test tracks or highways, exclusively on car-following and not considering lane changing. Therefore, SSMs that could report rear-end conflicts were chosen.

Consequently, we found multiple applications of TTC, DRAC, TTCD, RCRI, and MaxS for mixed traffic safety assessment using real-world data. In addition, researchers have used DV to capture the dangerous variations in vehicle kinematic parameters through statistical dispersal measures such as standard deviation and coefficient of variation [44], [72]. Our review also found that lane-changing effects were strictly considered in simulations environments. **Figure 3(b)** shows that most mixed traffic safety assessment studies were conducted on freeways with and without dedicated lanes (DLs) (49%) and on arterials (21%). Study of signalized intersections and roundabouts each comprised 13%, while hardly any research was conducted on alternative intersections.



(a): Study platforms reviewed

(b): Facilities reviewed

FIGURE 3. Study platforms and facilities reviewed.

C. REVIEW OF SSM THRESHOLD SETTINGS

Traffic conflict reporting by individual SSMs is threshold dependent. Different studies have used different threshold values considering the diversity of roads, driver types, participating road users, and vehicle types. As mentioned earlier, TSSMs cannot flag a traffic interaction as a traffic conflict unless a threshold is defined. For TVs, the threshold selection of TSSMs relies on the value of the RT of drivers, while for AVs and CAVs, the threshold selection relies on the RT (sensing, communication, and mechanical delays) of the vehicles. Our review found that the TTC threshold preferences typically vary between 1.5 and 4 seconds for TVs [33].

Most of the reviewed studies set the same TTC threshold for mixed traffic without considering the effect of vehicle technology. Many researchers employed the same 2 s TTC threshold [73], [74] and 1.5 s [75], [76], [77] for different types of vehicles operating in mixed traffic situations (**see Appendix found within the supplementary files on IEEE Xplore**). A few researchers used different TTC thresholds based on the car following situations; however, no justification of the threshold value selection was cited. For example, Virdi et al. [78] employed two different TTC thresholds for two different car-following scenarios. The authors assumed a threshold of 0.75 s when a CAV was the following vehicle and 1.5 s when a TV was the following vehicle. Conversely, Sinha et al. [75] assumed no traffic conflicts when CAVs were the following vehicles. However, when a TV was the following vehicle, they set the TTC threshold to 1.5 s. Rahman and Abdel-Aty [42] justified using the same TTC threshold selection for all types of vehicles operating in a mixed traffic scenario via sensitivity analysis and demonstrated that TTC threshold selection (from 1s to 3 s) had a minor effect on the resulting number of traffic conflicts. Many researchers use the same strategy to justify using the same TTC thresholds for all types of vehicles operating in a mixed traffic situation [42], [74], [79].

Furthermore, Ye and Yamamoto [46] did not consider any TTC threshold. Instead, the authors showed that the distribution of TTC values for different mixed traffic conditions varied based on the market penetration rate of CAVs. They also reported the TTC_{min} to demonstrate the conflict severity of a particular mixed traffic condition. Though the study gave an overview of the driving safety conditions of mixed traffic, it was impossible to report the number of conflicts without a threshold value. Similar to TTC, the PET threshold depends on the RT of drivers/vehicles. Archer [80] used a PET threshold value of 1.0 s. Interestingly, a handful of researchers used a longer PET threshold of 5 s to define risky situations [75], [76]. However, no justification for this relatively large threshold was documented. Similar to TTC, researchers of mixed traffic safety used the same PET threshold for all vehicle types, though the RT for TVs, CAVs, and AVs is likely different.

Our review found that the DRAC threshold ranges from 3 m/s^2 to 3.40 m/s^2. For example, AASHTO [81] recommends a DRAC threshold of 3.40 m/s^2. Similarly, Archer [80] proposed that if a vehicle braking exceeds 3.35 m/s^2, it should be reported as a conflict, consistent with the AASHTO recommendations. Research by Xie et al. [35] used a different DRAC threshold of 3.0 m/s^2 to report traffic conflicts of a real-world CV data. Although the authors used a lower DRAC threshold of 3.0 m/s^2, they did not justify their decision.

In summary, no consensus exists for selecting the SSM thresholds. Nonetheless, the outcome of traffic conflict analysis relies heavily on threshold selection. Songchitruksa & Zha [82] noted that using the traditional TTC threshold of 1.5 s produced eight times more conflicts than a threshold of 1.0 s in the safety assessment of CVs. This result demonstrates the importance of selecting the proper threshold for traffic conflict reporting by individual SSMs.

Our review found that the traffic environment can also affect the SSM threshold selection. Arun et al. [12] found that in organized traffic environments, the ordered nature of traffic flows makes it easier to correctly measure speed and distance, a requirement for TTC calculation. Conflict studies in less-organized traffic situations must rely on manual conflict detection methods, and typically use higher TTC thresholds to account for human error. In addition, thresholds are indicative of the safe limit of driving capabilities. Therefore, in the case of AVs and CAVs and their interaction with TVs, a justified threshold selection process is required. Further research is needed on developing a defensible framework for determining SSM thresholds based on the road facility type and the traffic mix.

D. FINDINGS FROM THE CASE STUDY

The goal of the case study analysis is to draw general inferences on the use of SSMs for mixed traffic safety assessment by analyzing different car-following scenarios as described in section II-B.

1) COMBINING SSMs IS MORE EFFECTIVE THAN USING A SINGLE SSM FOR TRAFFIC CONFLICT REPORTING

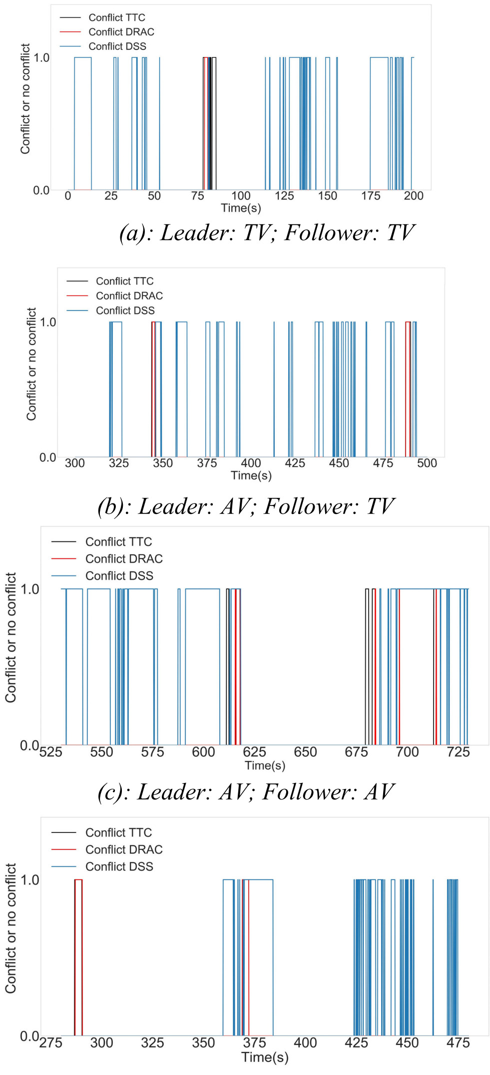
Figure 4 (a-d) depicts the reported case study scenarios of traffic conflicts using three different SSMs. The four figures show different time intervals with similar duration (200 s). We chose different time intervals because not all time intervals had reported traffic conflicts. **Figure 4 (a-d)** shows that traffic conflicts reported by a single SSM may not accurately reflect the overall safety of the investigated cases. For example, **Figure 4 (a)** shows that according to difference of space distance and stopping distance (DSS), the traffic interaction from 5-20 s is flagged as traffic conflict. However, neither DRAC nor TTC flagged it as such. This occurs because each SSM has its own definition and measurement methodology. However, the traffic interaction from 77-80 s is flagged as a traffic conflict by all three SSMs, increasing confidence in assessing a potential conflict.

We see similar findings from **Figure 4 (b-d)**. For example, **Figure 4 (c)** shows that the traffic interaction from 615-618 s was flagged as a traffic conflict by all three SSMs, giving the analyst a higher confidence in the actual conflict occurrence. The same observation can be made in **Figure 4(d)** in the period 370-374s. Though DSS, DRAC, and TTC measure rear-end traffic conflicts, they did identify different time steps as traffic conflicts. In addition, **Figure 4** makes clear that DSSMs (DSS) tend to report a lot more traffic conflicts than temporal TSSMs (TTC) and DeSSMs (DRAC).

Some researchers have combined SSMs to report traffic conflicts. For example, Ding et al. [47] used TTC, TIT, TET, and ADR to report traffic conflicts. However, they did not explain the motivation for the selected four out of the dozens of SSMs available. Similarly, Guériau and Dusparic [83] chose TTC and PET to report traffic conflicts without justifying their choice of SSMs. In fact, our review found that no collective guidance exists to propose the best set of SSMs that can accurately report traffic conflicts considering the different traffic facilities and vehicle composition. As a result, the use of SSMs in traffic safety studies is hampered by the lack of an overarching framework.

2) DISCOUNTING ACCELERATION AND DECELERATION VARIATIONS WITHIN AN INTERVAL YIELDS FEWER TRAFFIC CONFLICT REPORTS

Our review found that TTC and DRAC generally report fewer traffic conflicts because both assume that within a considered interval of time, the acceleration or deceleration of the subject vehicle pairs will remain unchanged. Our case study confirms those findings. **Figure 5 (a-d)** shows that TTC and DRAC reported fewer traffic conflicts than MTTC in all car-following scenarios. MTTC considers acceleration or deceleration discrepancies of the vehicles within considered interval of time. Our analysis also found that distance-based



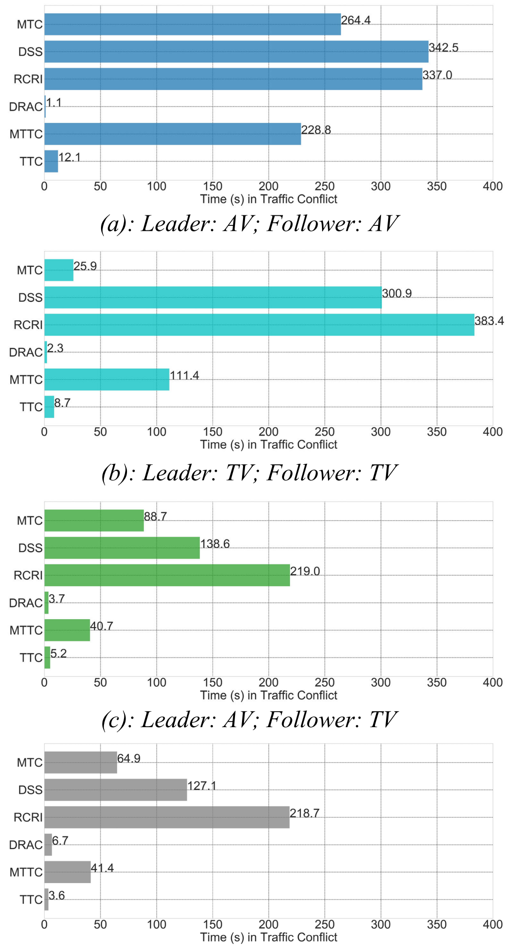
(a): Leader: TV; Follower: TV

(b): Leader: AV; Follower: TV

(c): Leader: AV; Follower: AV

(d): Leader: TV; Follower: AV

FIGURE 4. **Conflict reporting profile via 3 SSMs.**



(a): Leader: AV; Follower: AV

(b): Leader: TV; Follower: TV

(c): Leader: AV; Follower: TV

(d): Leader: TV; Follower: AV

FIGURE 5. **Reported duration in conflict by car following scenario and SSM.**

SSMs are less affected by acceleration or deceleration discrepancies.

3) THE ROLE OF RESPONSE TIME

Our analysis revealed that SSMs' traffic conflict reporting depends on the assumed RT values. The case study analysis corroborates our review finding that increasing the RT assumption by 0.5s for TV-TV scenarios increased the number of traffic conflicts reported by RCRI by 50%, DSS by 35%, and margin to collision (MTC) by 42%. We observed a similar trend for all other scenarios as well. Therefore, we recommend estimating RT for all vehicles involved (e.g., TVs, AVs, CAVs), rather than assuming a fixed value, to enable accurate traffic conflict reporting.

IV. DISCUSSION AND FUTURE DIRECTIONS

This paper reviewed the SSMs and SSM-based models used in mixed traffic safety assessment studies. In addition, we analyzed a real-world case study using mixed-traffic platoons comprising AVs and TVs to draw general inferences on the use of individual SSMs for mixed-traffic safety analysis. The review of literature and case study analysis have identified several limitations and research needs in the current literature. Those are briefly discussed below.

A. SSMs SHORTCOMINGS IN MIXED TRAFFIC SAFETY LITERATURE

This subsection discusses limitations in existing research practices for assessing mixed traffic safety using SSMs.

1) SIMULATION-BASED STUDIES LACK PROPER REPRESENTATION OF UNSAFE DRIVING

Most reviewed mixed-traffic safety assessment studies were simulation-based, per **Figure 3 (a)**. Simulation models tend to replicate safe driving behavior, not aberrant driving behavior. As a result, simulation platforms cannot simulate intense and dangerous vehicle interactions [83].

Simulation platforms use car-following models and lane changing models to represent the driving behavior. All car-following and lane-changing models used in simulation platforms (e.g., Wiedemann 99, Intelligent Driving Model (IDM), Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC)) are coded to be collision-free. For example, SUMO [84] uses the ACC car-following model [85] to represent AV car-following. SUMO uses a collision avoidance mode so that the AV car-following remains collision-free. To illustrate using the ACC car-following model, AV acceleration is a function of gap error and speed difference with the preceding vehicle. When the distance of the subject AV with the preceding vehicle is below 100 m, the speed difference between the AV and its preceding vehicle is less than 0.1 m/s, and the gap error is negative, the following vehicle will activate the collision avoidance mode. In this mode, the following AV will use emergency deceleration to avoid collision [84].

Furthermore, current simulation tools lack the adjustments to driving behavior related to road geometry, which may lead to traffic collisions. For example, most of the micro-simulation platforms (e.g., VISSIM) use links and connectors to direct traffic flow. In a case where connectors of two opposing left turn at an intersection are created without overlapping opposing left-turn paths, no chance exists for the opposing left turns to experience head-on conflicts. In the real world, drivers may not strictly follow lane markings. Therefore, applying SSM in the simulation platform may ignore these potential conflicts.

2) MICRO-SIMULATION MIXED TRAFFIC STUDIES LACK PROPER CALIBRATION

Our review found that about 30% of existing simulation studies did not report any calibration efforts, while the rest included calibration with traditional vehicle traffic streams only. The paucity of mixed traffic data makes the calibration and validation process for mixed traffic safety simulation challenging. However, safety assessment using SSM lacking proper calibration may produce misleading conclusions [15]. As an example, if DRAC is used as an SSM and applied to a simulated trajectory, the acceleration profile of the real-world and simulated data should be similar. However, Das et al. found that the default parameter values of the ACC model [86] generate trajectories with significantly different acceleration profiles from real-world acceleration profiles. Thus, SSM should only be used for assessing mixed traffic once thorough calibration and validation have been completed.

3) INABILITY TO CAPTURE BEHAVIORAL HETEROGENEITY

Individual SSMs and SSM-based models cannot capture unobserved vehicular heterogeneity. Traffic conflicts are extracted from vehicular trajectories that show vehicular position over time. However, many other unobserved factors can contribute to traffic conflicts that cannot be captured through individual SSMs or SSM-based models. For example, in mixed traffic, the design variations of AVs posed by different manufacturers may cause unobserved heterogeneity. In addition, the interaction of AVs or CAVs with TVs may be affected by driver age, occupation, and socio-demographic factors that are not observable by the current SSMs or SSM-based models. If we ignore unobserved heterogeneity, the SSM-based model will be incorrectly specified, and the estimated parameters will be biased and inaccurate, leading to flawed conclusions and estimates.

TABLE 2. Identified datasets with mixed vehicle fleet.

Dataset (Reference)	Vehicles involved	SAE AV automation level	Publicly Available
Knoop et al. [87]	AVs & TVs	Level 1	No
USDOT Carma [88]	AVs, CVs & CAVs	Level 1 & 2	Yes
Li et al. [89]	AVs & TVs	Level 1 & 2	Yes
OpenACC [27]	AVs & TVs	Level 1 & 2	Yes
THEA Connected Vehicle Pilot [90]	CVs & TVs	N/A	No

4) LACK OF REAL-WORLD DATA ON AV AND CAV LATERAL RESPONSE

Our review found only three publicly available datasets [27], [91], [92] as shown in **Table 2**. These datasets only comprise car-following trajectories and lack lane changing, merging, diverging, or weaving trajectories. Our review indicates that traffic conflicts related to lane changing comprise a significant portion of the total conflicts [15]. Consequently, a simulation model calibrated based exclusively on car-following trajectories will miss many of the traffic conflicts related to lane changes.

5) SHORTCOMINGS OF SSM-BASED MODELS

Some SSM-based models, such as the uncertainty model and EVT, can estimate a traffic conflict without explicitly setting thresholds, giving them a significant advantage over individual SSMs. Those models use a predefined statistical distribution to estimate traffic conflicts. For example, EVT model calibration uses traffic conflict extremes. These extreme observations are rare, especially when the conflict observation time is short. Due to this small sample size, the identified conflict extremes by either the BM approach or the POT approach may not represent the actual extremes [93]. Using non-real extremes for EVT model development violates the asymptotic assumption, the foundation of EVT. Consequently, the fitted parameters of the EVT distribution could be biased and less accurate due to the limited sample size. Thus, it is crucial to investigate how the sample size affects the statistical assumptions of the models. Based on our review regarding sample size, we find that it is also necessary to use an appropriate sample size of traffic conflicts to estimate an unbiased, accurate model [94].

Additionally, data-driven surrogate safety models (such as deep learning-based and fuzzy logic-based models) are now considered reliable means to report traffic conflicts. The ease of data collection and resulting abundance of fine-resolution data facilitate modeling traffic conflicts with data-driven models. Nonetheless, data-driven models are not without drawbacks. For example, deep learning models tend to overfit. Consequently, the proposed model correlates only within the range of the underlying dataset. Therefore, the transferability of the proposed model raises some questions. Another problem with deep learning algorithms is that they can map input and output well but do not understand well the context of the data.

Moreover, deep learning methods are still a black box; therefore, the explicability of these models is challenging. Conversely, a significant drawback of fuzzy logic control systems is that they depend entirely on human knowledge and expertise. Labeling the dependent variable is not binary and thus needs human justification to define the dependent variable. Therefore, the systems require a lot of testing for validation and verification. Additionally, all data-driven models depend on the accuracy of the data. Hence, it is necessary to check the validity and accuracy of the data before using it for modeling purposes.

B. RESEARCH NEEDS

As stated earlier, simulation models lack representation of anomalous driving behavior. Therefore, the outcome of simulation-based safety studies is also limited. Calibration through real-world car following and lane-changing mixed traffic data can mitigate this limitation. Recently several field studies on AV and CAV platooning have been conducted (e.g., CARMA, OpenACC). Unfortunately, most collected data are either protected by industry copyright or not publicly available. Consequently, researchers must still rely on simulation-based studies, which are also hindered by the lack of data. Therefore, it is important to grow the current set of field experiments with mixed traffic, including car following and lane-changing observations. It is also important to make those data publicly available.

1) EXPLORING THE VALIDITY OF CURRENT SSMs

Previous research expended substantial effort to justify using SSMs to assess traffic safety [5], [95]; however, those efforts focused exclusively on homogenous TV streams. It is unclear whether SSMs validated for a TV traffic stream are applicable to mixed traffic. One straightforward way to validate an SSM is to compare its frequency with crash data. However, historical crash data are absent for AVs and CAVs in a mixed traffic stream. In addition, the response of AVs and CAVs is expected to differ from TVs, depending on their automation levels. We reviewed ten current ACC-equipped AVs by different manufacturers and found that users of ACC-equipped vehicles can choose their driving mode. For example, the 2021 Honda Civic has four different gap setting options (short, middle, long, and extra-long), ranging from 1.1s to 2.9s [96], whereas, a 2021 Cadillac XT4 has three different gap options ranging from 1.1s to 2.5 s [97]. In reality, conservative time gap driving in a Honda AV is unlikely to be equivalent to conservative time gap driving in a Cadillac AV. Thus, AVs and CAVs can have different driving styles and desired time gaps, even within the same automation levels.

Furthermore, TV drivers may behave differently in the presence of CAVs and AVs in the traffic stream. Therefore, it is advisable to set a standard of SSMs in mixed traffic that can account for the different traffic scenarios, automation levels, and driving styles. As such, existing SSMs and corresponding thresholds may require some revision. For instance, the TTC threshold of 1.5s or the DRAC threshold of 3.35 m/s^2 must be evaluated to determine if they will still work in a mixed traffic scenario. The question remains whether TV-based SSM models are applicable under mixed traffic conditions.

2) EXPLORING THE SUITABILITY OF SSMs BY FACILITY TYPE

The accuracy of the traffic conflict reporting by SSMs depends on the type of facilities considered. For example, detecting rear-end and right-angle conflicts is vital to assess traffic safety at signalized intersections. Our review found that studies on signalized intersections used SSMs that are efficient in rear-end and right-angle conflict reporting. TTC and DRAC can report rear-end and head-on traffic conflicts, whereas PET reports right-angle traffic conflicts. Our review also found that TTC, PET, and DRAC were the most frequently used SSMs in the safety assessment of signalized intersections. Conversely, roundabouts eliminate all straight-line interactions between the vehicles except on the approaches [11]. Therefore, PET was the most frequently used SSM for encroaching type traffic conflict reporting for roundabouts. Overall, the field lacks clear recommendations on which set of SSMs should be applied based on the type of facility being examined.

3) EXPLORING THE SUITABILITY OF SSMs BY ROAD USERS INVOLVED

The suitability of SSM selection also depends on the road users involved. For example, Tageldin and Sayed [98] studied pedestrian-vehicle conflicts in five cities—New York, New Delhi, Shanghai, Vancouver, and Doha—and found that TSSMs such as TTC were useful for traffic conflict detection in the organized traffic environments of New York and Vancouver. However, they were less relevant as a traffic conflict measure in New Delhi's less-organized traffic environments. The authors also concluded that TTC could not measure conflicts in a non-lane discipline-based traffic environment. Jhonson et al. [10] reviewed several SSMs for characterizing traffic conflicts involving pedestrians and found that no universal SSM can meet all the distinct conditions under various application contexts. Thus, they favor selecting SSMs based on the application context. Finally, Zheng et al. [93] also observed the lack of consensus on a standard set of SSMs and suggested that appropriate SSMs may vary by involved road users. Thus, a lack of clear guidance prevails on which set of SSMs to use depending on the road users involved. In addition, in our review, we observed a dearth of research on the safety of vulnerable road users (e.g., pedestrians, bicyclists, and disabled people) in mixed-traffic settings.

4) APPLICATION OF DRIVING SAFETY FIELD METHODS

The driving safety field method considers the interaction among the behavioral field, kinetic field and static field while assessing road safety [99]. Nonmoving road objects, such as a stopped vehicle, determine the static field. The kinetic field includes the moving objects on roads, such as vehicles and pedestrians. The individual characteristics of drivers determine the behavioral field. SSMs only consider the kinetic component by analyzing the trajectories of an interacting vehicle pair, ignoring the static and behavioral parts of road safety assessment. In addition, SSMs are usually selected based on the scope of the study and methodological suitability, making it difficult to generalize the results [100]. Mixed traffic has brought significant heterogeneity to the behavioral and kinetic fields. Our review found no application of driving safety field methods while assessing mixed traffic safety. Therefore, applying the driving safety field in mixed traffic safety assessment may be a promising direction for future research.

5) DEVELOPING THE CAPABILITY FOR REAL TIME TRAFFIC CONFLICT DETECTION

Detecting traffic conflicts in real time may assist authorities in better managing their transportation network safety through proactive risk mitigation measures like real-time signal optimization at signalized crossings or traffic demand management on freeways. Crashes on major arterials or freeways in peak hours can cause significant increases in both travel time and vehicular emissions. In addition, the early mix of AVs and TVs is likely to result in a highly dynamic traffic situation in which human driver behavior is likely to be temporally unstable and constantly evolving [101]. Therefore, research focused on real-time traffic conflict detection will have far-reaching implications in improving overall traffic flow along with vehicle emission profiles.

V. SUMMARY AND CONCLUSION

The market penetration of AVs on the road fleet is steadily rising. Additionally, much research progress has been made on AV safety in the past few years. The potential for traffic conflict-based analysis to enhance traffic safety has prompted a slew of research over the last decade aiming to identify traffic conflicts more accurately for mixed traffic. However, a comprehensive review of SSMs for mixed traffic conflict assessment needs to be included, which this paper addresses.

This study categorized individual SSMs into five classes: time-based, distance-based, deceleration-based, energy-based, and combined. Furthermore, SSM-based models are categorized into six classes: uncertainty model, extreme value theory model, causal and counterfactual model, surrogate safety assessment model, deep learning and machine learning-based surrogate safety models, and fuzzy logic-based surrogate safety models. In addition, the research highlighted SSMs and SSM-based models' application in mixed traffic and uncovered some critical research gaps. A significant gap is the lack of robust SSM threshold selection criteria. Our review also uncovered inconsistency in selecting SSM threshold values and a lack of convincing evidence for selecting a particular SSM threshold. In addition, our review found that the current SSMs have been validated mostly under traditional vehicle traffic streams. Since mixed traffic crash data are scarce, the validity of the current SSMs and corresponding thresholds have yet to be proven adequate for mixed traffic conditions.

The scarcity of real-world mixed traffic data comprising different traffic mixes, connectivity, and automation has also hindered our ability to validate the utility of SSMs for mixed traffic. Our review found that real-world mixed traffic data scarcity compelled researchers to rely on simulation-based studies. The validity of simulation studies involving equipped vehicles (AVs, CAVs, and CVs) is challenged due to the lack of real-world calibration and validation datasets. Additionally, simulation-based studies often lack in accurately representing anomalous driving behavior that can cause safety hazards.

Our analysis found that the use of a combination of SSMs is generally more effective in traffic conflict reporting than using a single SSM. However, no method currently exists to determine how to select and combine multiple SSMs based on facility and road user type. Our review found little guidance on selecting SSMs or SSM-based models based on different road users or facility types. Applying context-appropriate SSMs and corresponding thresholds can be the key to delivering conflict-based analysis that contributes significantly to our understanding of traffic safety.

There are several limitations of this study that must be acknowledged. The experimental case study was restricted to SAE level 2 ACC-equipped vehicles with no lane-changing information. Thus, traffic conflicts introduced by improper lane changes were not investigated. Furthermore, the results were limited to a restricted set of settings (e.g., short time gap settings for AVs) and field tests (e.g., no disturbance from surrounding vehicles). Tests were always scheduled for non-peak hours in particular scenarios. Moreover, the mixed traffic studied only had AVs and TVs.

Finally, despite the substantial documented progress in developing and implementing various SSMs in mixed traffic, significant opportunities remain to enhance the use of the reviewed methodologies. This research proposes several avenues for further traffic-conflict investigation and applications in mixed traffic.

DECLARATION OF INTEREST

The authors state that they have no known competing financial interests or personal ties that could have influenced the research presented in this study.

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TANMAY DAS was born in Bangladesh. He received the B.S. and M.S. degrees in civil engineering from the Bangladesh University of Engineering and Technology, in 2015 and 2017, respectively. He is currently pursuing the Ph.D. degree with the Civil Construction and Environmental Engineering Department, North Carolina State (NC State) University.

He undertakes independent research on autonomous vehicle safety and mobility. He is experienced in data cleaning, data analysis, micro-simulation, writing, and editing technical reports. He is currently a Graduate Researcher on projects funded by the U.S. Department of Transportation (USDOT), Southeastern Transportation Research, Innovation, Development and Education Center (STRIDE), and the North Carolina Department of Transportation (NCDOT). He has authored or coauthored more than a dozen peer-reviewed journal articles and conference proceedings. His research interests include problem-solving, critical thinking, and working in groups.

Mr. Das is an active member of the American Society of Civil Engineers (ASCE) and Friend of Transportation Research Board Subcommittee on Connected and Automated Traffic Flow.

M. SHOAIB SAMANDAR received the M.S. and Ph.D. degrees in civil engineering from North Carolina State (NC State) University, Raleigh, in 2015 and 2019, respectively, with a focus on intelligent transportation systems.

From 2010 to 2015, he worked on behalf of USACE in different capacities. Since 2019, he has been a Research Scholar with the Institute for Transportation Research and Education, NC State University. He has authored or coauthored over a dozen peer-reviewed publications. His research interests include intelligent transportation systems, connected-autonomous vehicles, and the application of artificial intelligence to the transportation domain.

MEAGAN KITTLE AUTRY received the Ph.D. degree in technical communication from North Carolina State (NC State) University, Raleigh, NC, USA, in 2013. She is currently an Assistant Teaching Professor with the Department of Civil, Construction, and Environmental Engineering, NC State University.

NAGUI M. ROUPHAIL was born in Cairo, Egypt, in 1950. He received the B.Sc. degree in civil engineering from Cairo University, in 1972, and the M.S. and Ph.D. degrees in transportation engineering from The Ohio State University, in 1977 and 1981, respectively. From 1981 to 1993, he was an Assistant Professor and then an Associate Professor in civil engineering with the University of Illinois Chicago (UIC), where he was also a Faculty Member (affiliate) of the Urban Transportation Center. In 1994, he was recruited as a Professor in civil engineering with North Carolina State University, Raleigh, where he led the Transportation Systems Research Group, Department of Civil, Construction and Environmental Engineering, until 2001. He was appointed as the Director of the Institute for Transportation Research and Education (ITRE), a role he assumed successfully until stepping down, in 2016. He returned to his home department for another four years and was awarded the position of a Distinguished University Professor prior to his retirement, in June 2020. He was also employed by Kittelson and Associates as a Senior Principal Engineer on a part-time basis. He has authored or coauthored over 200 refereed journal publications and developed research collaborative initiatives in several countries in Europe, Asia, and Africa. His research interests include traffic operations, with a focus on analytical modeling and simulation. He was a recipient of 13 best paper awards by TRB, ASCE, and ITE, including the prestigious Grant Mickle Award by TRB, in 2010.