Quantifying Autonomous Vehicle Safety: A Scoping Review of the Literature, Evaluation of Methods, and Directions for Future Research

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ABSTRACT

The safety of autonomous vehicles (AVs) must be validated not only for market success but also for more informed decision-making about AV implementations and supporting policies and regulations to govern the unintended consequences of AVs. This study employed a scoping review methodology to identify the approaches used in the literature to quantify the safety of AVs. As a result, six approaches were identified: target crash population, traffic simulation, driving simulator, road test data analysis, system failure risk assessment, and safety effectiveness estimation. After screening and reviewing the literature of the identified approaches, first, we investigated each approach in terms of its input, output, and application to estimate AV safety implications at the vehicle, transportation system, and society levels. Second, we qualitatively compared them in terms of three criteria: availability of input data, suitability for evaluating different levels of automation, and reliability of estimations. We further identified four challenges in AV safety validation: (a) shortcomings in methodology for validating and measuring AV safety, (b) effects of changes in travel patterns and urban areas on AV safety, (c) potential risky behavior of users, and (d) emerging safety issues such as cybersecurity. The comparison between quantification approaches can help researchers select the most appropriate method based on their desired study objectives and limitations. Future research is required to address the identified challenges in the safety evaluation of AVs.

Keywords: Autonomous vehicle; Safety validation; Safety implications; Driving simulator; Traffic simulation; Road test data; Target crash population; Safety effectiveness; Failure risk

1. Introduction

Autonomous vehicles (AVs) have the potential to profoundly improve traffic safety, mainly by eliminating driver error. According to the National Highway Traffic Safety Administration (NHTSA), human error contributes to 94% of crashes, and AVs are optimistically expected to prevent these crashes (NHTSA, 2018). Nevertheless, more accurate AV safety evaluations are required before deploying AVs. Particularly, the intent to use AVs and their market success are contingent upon the safety validation of AVs (Sener et al., 2019). In addition, not only can manufacturers and the automotive industry benefit from the accurate safety evaluations of AVs, but legislative and executive agencies require such information to advocate with industry stakeholders and society (Junietz et al., 2018). Evaluating the safety implications of AVs is necessary for formulating regulations and policies to alleviate the unintended consequences of AV implementations and increase their benefits, as outlined by the US Department of Transportation (US DOT, (US DOT, 2018)) and the US Congressional Research Service—a public policy research institute of Congress (Canis, 2020).

Given the significant role of safety validation in the successful and efficient implementation of AVs, quantification studies are needed to evaluate AV safety. This study was designed to synthesize the lessons learned from existing studies that quantified the safety of AVs. To this end, we implemented a scoping review methodology to identify, screen, and review the existing literature about quantification of AVs' impacts on traffic safety. After identifying quantification methods, we ran two evaluations to compare the quantification methods. First, we investigated each approach in terms of its input, output, and application to estimate AV safety implications at the vehicle, transportation system, and society levels. Second, we compared the identified approaches based on three criteria: availability of input data, suitability for evaluating different levels of automation, and reliability of estimations. Then, we identified and discussed the gaps in the literature and AV safety validation challenges that need to be addressed in the future. We expect this study to serve as a stop knowledge point and unveil the avenues that future research can take to contribute to AV safety validation. The results of evaluating AV quantification methods can help researchers, policy makers, and practitioners choose an appropriate evaluation method based on their objective. This study did not examine nominal safety or perceived safety but rather targeted the substantive safety of AVs. Nominal safety refers to whether or not a vehicle is fulfilling all standards and laws that apply to the vehicle. The perceived safety of a vehicle is how the general public experiences the safety of the vehicle. Moreover, this study was not intended to synthesize the results of the quantification methods for evaluating AV safety but rather to explore the methodologies.

2. Background Information

2.1. Safety Implications at Different Automation Levels

AV safety and the related safety implication complexity vary in terms of driving automation levels, as defined by the Society of Automobile Engineers (SAE, (SAE, 2018)). In the lower levels of automation (Levels 1 and 2), the driver is responsible for dynamic driving tasks (DDTs), and an advanced driver assistance system (ADAS) on the vehicle can sometimes assist the human driver with either steering or braking/accelerating (SAE, 2018). ADASs have the potential to prevent or mitigate crashes by partially eliminating driver error. In higher levels of automation, the automated driving system (ADS) performs the entire DDT while engaged. In Level 3, the DDT fallback-ready user needs to intervene when requested (SAE, 2018). On the other hand, Levels 4 and 5 automation do not require a DDT fallback-ready user, and Level 5 has an unlimited operation design domain (ODD). An ADS is expected to entirely eliminate driver error; however, disengagement from ADSs and DDT fallback can be challenging.

2.2. Levels of Safety Implications

AV impacts on safety can be investigated at three levels: vehicle, transportation system, and society (Figure 1). At the vehicle level, AVs can be examined in terms of how they contribute to the critical driver-related reasons for crashes, such as inattention; internal and external distractions; inadequate surveillance; decision error caused by false assumptions and perceptions; performance (i.e., execution of improper driver response); and nonperformance mainly due to impairment, drowsiness, and fatigue (NHTSA, 2018). AVs' implementation carries higher levels of uncertainty at the transportation system level. AVs safety can be examined based on their potential to reduce traffic conflicts and, consequently, reduce crashes. At the society level, crashes pose a public health crisis, and investigation of AVs can focus on their potential to promote public health by reducing crashes (Sohrabi et al., 2020). Previously, the role of motor vehicle crashes in public health has been measured in the form of premature mortalities from fatality crashes (Sohrabi and Khreis, 2020) and the disability-adjusted life year from injury crashes (Tainio, 2015).

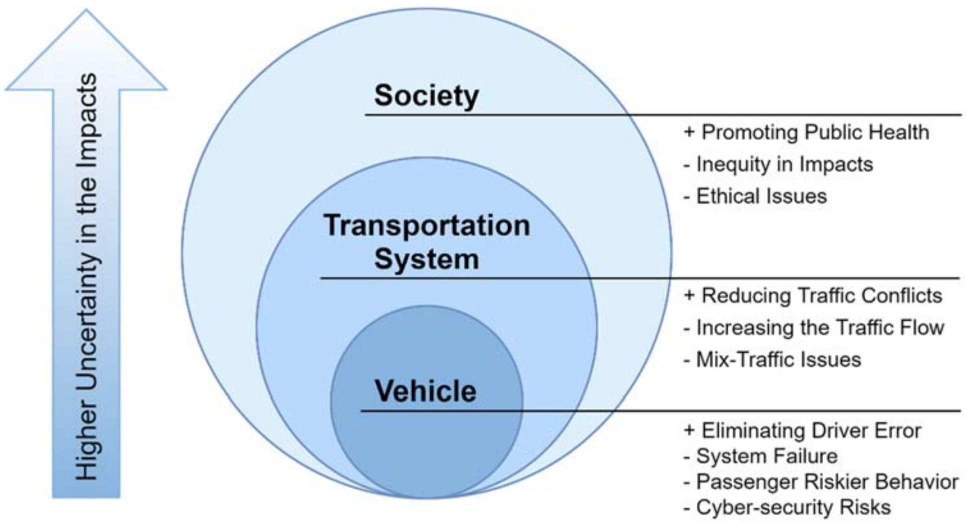

Figure 1. Levels of AV safety implications

Although traffic crashes caused by driver error are expected to be eliminated after the deployment of AVs, other safety issues may compromise the positive impacts (Kockelman et al., 2016, Litman, 2017, Yang et al., 2017). System operation failure (Koopman and Wagner, 2016), cybersecurity (Lee, 2017), and passengers' risky behaviors related to feeling overly safe while using AVs are some examples of potential safety concerns at the vehicle level. At the transportation system level, AVs may experience safety issues related to the interaction between human drivers and AVs in mixed traffic (Virdi et al., 2019, Taeihagh and Lim, 2018), as well as AVs' potential to increase traffic flow and, consequently, exposure to crashes as a result of induced demand, increased mobility, and changes in land use (Milakis et al., 2017). Moreover, due to the high cost of AVs, only wealthy consumers might be able to afford AVs as personal vehicles (Raj et al., 2019, Cohen and Shirazi, 2017), so the disproportionate deployment of AVs may lead to health inequities that challenge AV safety impacts at the society level. The controversial discussion about how AVs should react during an unavoidable crash is another example of AV safety challenges at the society level.

3. Methodology

We followed a scoping review methodology proposed by Arksey and O'Malley (2005) to (a) examine the nature of previous studies on quantifying the impacts of AVs on traffic safety, (b) summarize and document findings of previous research, and (c) identify research gaps in the existing literature. In this study, we chose to conduct a scoping review since we aimed to identify previous studies answering a general question and then review the evidence from previous quantifications on the impact of AVs on traffic safety (Munn et al., 2018). In this context, the findings are not aggregated, nor is the quality of evidence assessed (Arksey and O'Malley, 2005). In the following sections, we discuss the scoping review methodology and the results of the review.

3.1. Review Question

The first step in a scoping review is to identify a research question to be answered (Arksey and O'Malley, 2005). The research question for this review was the following: "What are the methodologies and the gaps in the existing research on quantifying the potential impacts of AVs on traffic safety?" We were specifically interested in research that quantified the impacts of AVs rather than studies of a speculative nature. We also aimed to explore the results of previous research and identify existing gaps.

3.2. Identifying Relevant Studies

A search strategy was developed to retrieve relevant research evidence from four electronic databases—Scopus, Web of Science, Transport Research International Documentation (TRID), and IEEE Xplore—as well as reference lists of the retrieved publications. The databases were searched to identify published articles, letters, reports, book chapters, and books using any combination of two sets of keywords in their title, abstract, and keywords: ["autonomous vehicle" or "autonomous car" or "self-driving car" or "driverless car" or "automated driving"] and ["crashes" or "accidents" or "collision" or "safety"]. We included only published material written in English due to the burdensome translating process. All material considered in the review was published as of April 2020.

3.3. Study Selection

To ensure consistency in the selection of studies that answered the review's question and to exclude irrelevant studies, we defined a set of inclusion and exclusion criteria. The criteria implemented for the study selection were fourfold:

1. The studies had to explicitly quantify the impacts of AVs on traffic safety rather than be speculations and qualitative assessments.
2. The term *automated vehicle* had to represent a vehicle used for transportation, such as automated cars, buses, and trucks.
3. Studies about connected and autonomous vehicles (CAVs) that quantified the automated driving safety impacts were included (although the connected vehicles' [CVs'] safety impacts did not fall within the scope of this study).
4. Since we specifically targeted AV safety, the methodologies for evaluating ADAS safety were not included.

We selected relevant studies after applying the inclusion criteria to the identified publications. The selection process was divided into two stages. First, the titles and abstracts of the identified publications were reviewed, and potentially relevant publications were selected. Second, the full text of the potentially relevant publications was retrieved and reviewed against the inclusion criteria, and studies that did not meet all inclusion criteria were excluded. The reference lists of included publications were also reviewed to find any relevant articles that were not identified through the developed search strategy.

4. Results

4.1. Search Results

The implemented scoping review process is shown in Figure 2. A total of 1,448 publications were identified using the developed search strategy. After checking for duplicates, screening the identified articles, and reviewing articles' full text, we excluded 1,404 articles: 265 duplicates, 1,060 after screening, and 79 after full-text review. Ultimately, 44 articles met the inclusion criteria and were included in this review.

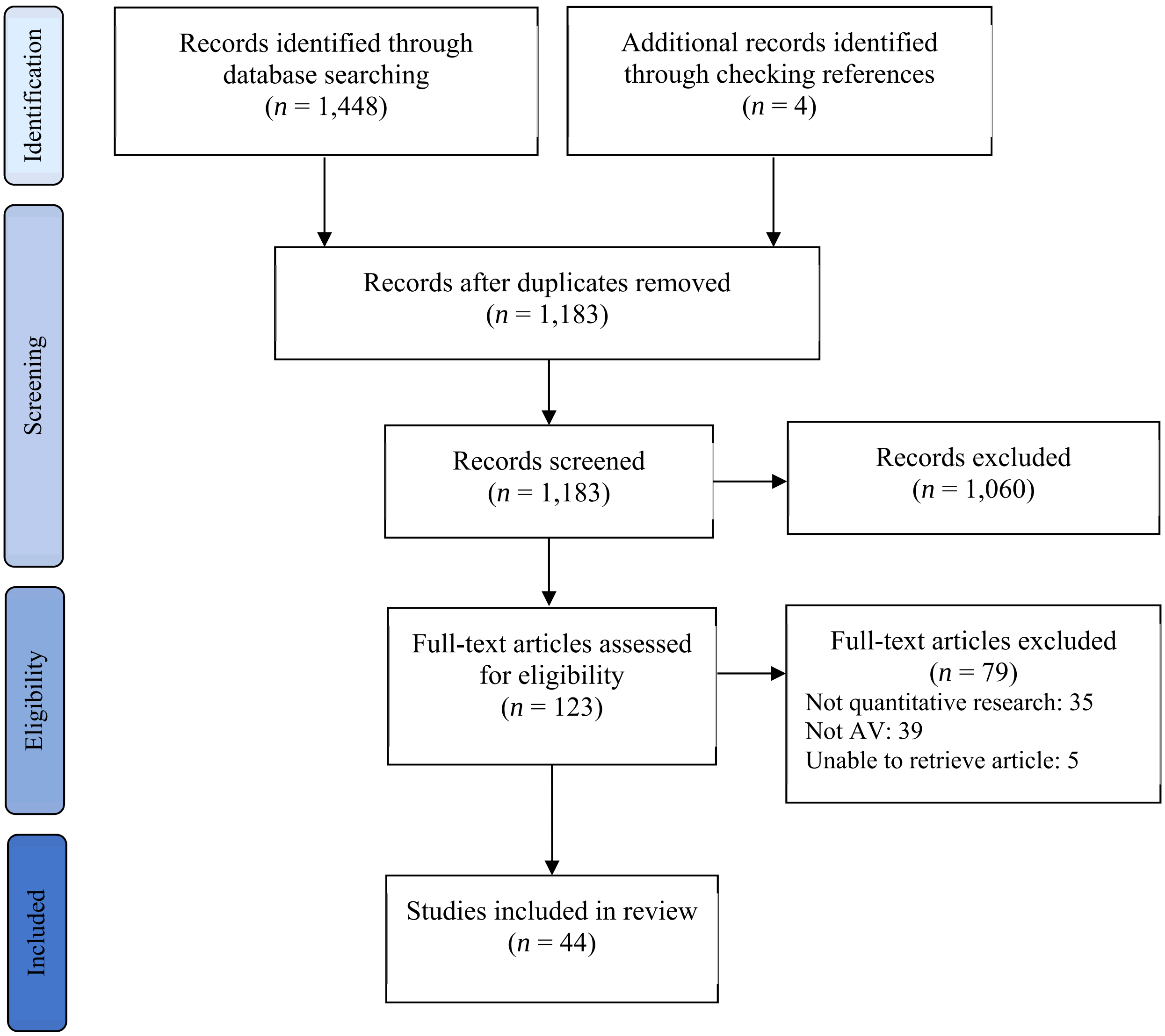

Figure 2. Study identification and selection mechanism of the implemented scoping review

4.2. Characteristics of Included Studies

The number of publications increased significantly beginning in 2012, although in 2019, only 14 articles were published on quantifying AV safety implications (Figure 3a). The AV safety quantification approaches can be classified into six groups: target crash population, traffic simulation, driving simulator, road test data analysis, system failure risk assessment, and safety effectiveness estimation. Figure 3b shows the distribution of evaluation approaches in the included studies in this review. Road test data analysis and simulation studies were more commonly used for evaluations, followed by the driving simulator and target crash population approaches. Failure risk assessment and safety effectiveness quantification received the least attention. A time-series analysis of publications indicated that traffic simulation and road test data analysis methods began receiving more attention over time. Increases in road test data may be one of the reasons behind this change.

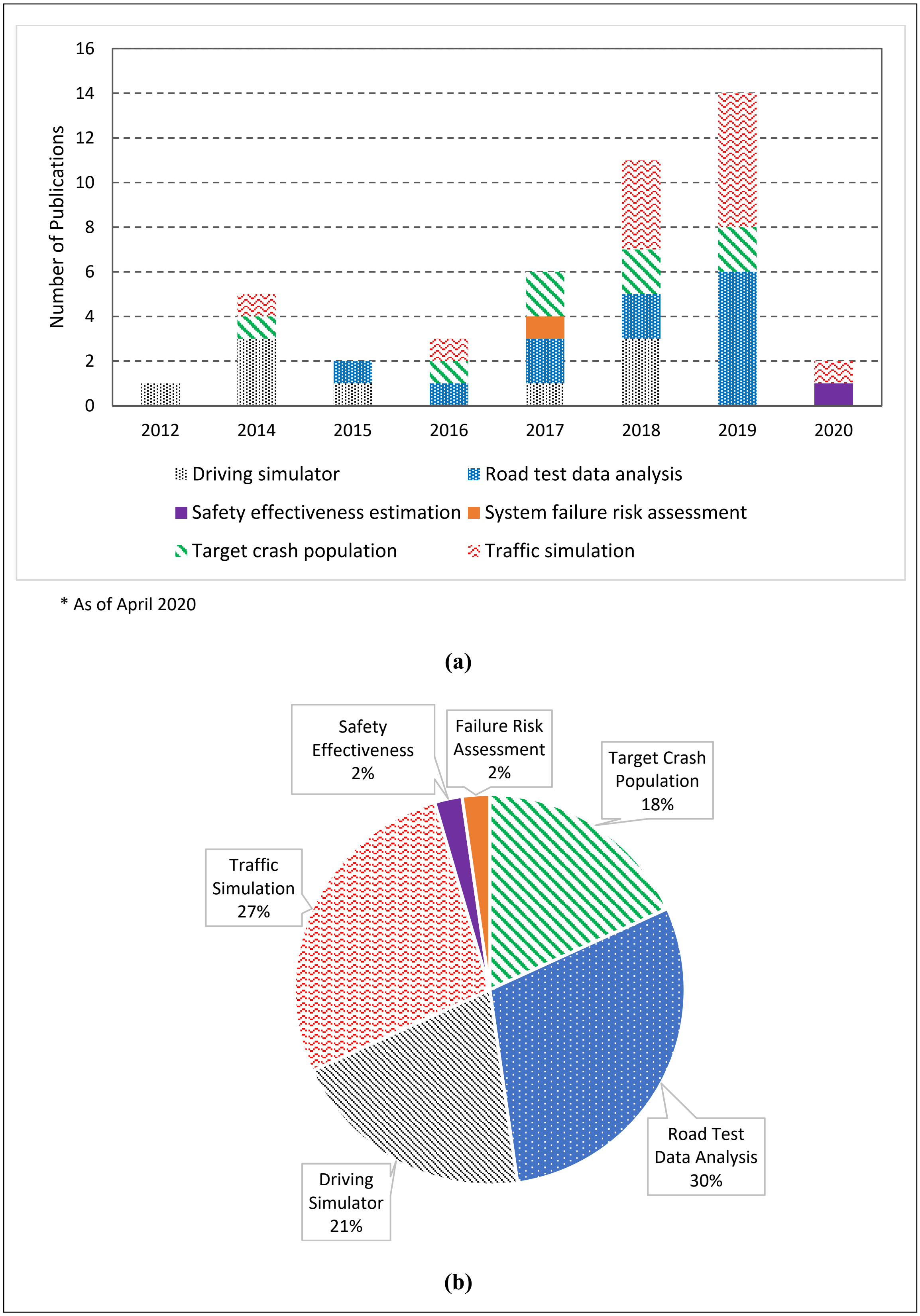

Figure 3. (a) Publication date of the studies included in this review, and (b) distribution of the identified AV safety evaluation approaches

4.3. Identified Approaches

In this section, we discuss the AV safety quantification approaches identified in the literature.

4.3.1. Target Crash Population

The target crash population approach quantifies the number of preventable crashes after AV implementation. The quantification process in the examined studies followed three steps (Rau et al., 2015, Yanagisawa et al., 2017):

1. Identify AVs' ADS and ADAS functionality.
2. Match AV functionality with the target crash type.
3. Explore the crash datasets and identify preventable crashes.

In the first step, AV functions were investigated on the basis of (a) levels of automation (Lubbe et al., 2018, Agriesti et al., 2019), and (b) individual or combined ADS and ADAS functions (Combs et al., 2019, Detwiller and Gabler, 2017, Hendrickson and Harper, 2018, Li and Kockelman, 2016, Kusano and Gabler, 2014).

In the second step, the AV functionality was matched with corresponding crash characteristics. Depending on the ADAS/ADS considered, studies assessed AV technology to mitigate either specific crash types (e.g., rear-end collision, pedestrian crashes) (Combs et al., 2019, Detwiller and Gabler, 2017, Hendrickson and Harper, 2018), specific crash-contributing factors (e.g., distracted driving, speeding, etc.), or critical pre-crash events (e.g., running a red light, vehicle failure) (Yanagisawa et al., 2017, Lubbe et al., 2018, Li and Kockelman, 2016, Kusano and Gabler, 2014). In addition, some AV functions are programmed to operate under a certain ODD to activate and achieve the maximum desired effectiveness; therefore, the crash dataset had to be filtered out to mirror those conditions properly. Lighting condition (day/night) (Yanagisawa et al., 2017, Agriesti et al., 2019), weather condition (clear/adverse) (Yanagisawa et al., 2017, Agriesti et al., 2019), road surface condition (wet/dry) (Yanagisawa et al., 2017, Agriesti et al., 2019), travel speed range (Yanagisawa et al., 2017, Agriesti et al., 2019, Hendrickson and Harper, 2018), visual obstruction (Lubbe et al., 2018, Combs et al., 2019), pedestrian crossing condition (Lubbe et al., 2018, Detwiller and Gabler, 2017), lane marking condition

(Lubbe et al., 2018, Agriesti et al., 2019), and stable vehicle condition (Lubbe et al., 2018) are conditions under which AV safety was examined in the literature. The AV safety implications were explored for various road facilities and areas (Detwiller and Gabler, 2017, Hendrickson and Harper, 2018) as well. However, in some studies, facility type was automatically filtered out by selecting possible crash scenarios (e.g., running red light, which is specific to intersections only) and beneficial safety equipment specific to that facility (e.g., cooperative intersection collision avoidance systems, which are applicable in intersections only) (Li and Kockelman, 2016, Kusano and Gabler, 2014). The safety effectiveness of AV technology was widely presumed to be 100% in the literature (Yanagisawa et al., 2017, Agriesti et al., 2019, Detwiller and Gabler, 2017, Hendrickson and Harper, 2018, Kusano and Gabler, 2014); however, some studies accounted for the shortcomings in the safety implications of AVs by considering the effectiveness of AV technology (Lubbe et al., 2018, Combs et al., 2019, Li and Kockelman, 2016). AV safety effectiveness was either extracted from simulation studies (Combs et al., 2019) or indirectly through defining different sets of rules (Lubbe et al., 2018, Li and Kockelman, 2016). Each set consisted of assumptions regarding weather, road condition, vehicle condition, speed range, and so forth, through which both maximum effectiveness and lower effectiveness due to adverse conditions could be taken into account. Moreover, different rule sets provided a lower and upper bound for the expected number of preventable crashes instead of a constant value for effectiveness. Most of the literature assumed a 100% market penetration rate (MPR); indeed, only two studies considered the MPR in their analysis (Agriesti et al., 2019, Li and Kockelman, 2016).

In the third step, the crash datasets were explored, and the crash characteristics were extracted. Next, the safety benefits of AVs were quantified in terms of the number of preventable crashes (Yanagisawa et al., 2017, Lubbe et al., 2018, Agriesti et al., 2019, Combs et al., 2019, Detwiller and Gabler, 2017, Hendrickson and Harper, 2018, Kusano and Gabler, 2014) and/or reduced cost of crashes (Yanagisawa et al., 2017, Hendrickson and Harper, 2018, Li and Kockelman, 2016). As a result, AV safety was attributed to ADSs (Yanagisawa et al., 2017, Lubbe et al., 2018, Agriesti et al., 2019, Combs et al., 2019, Detwiller and Gabler, 2017, Hendrickson and Harper, 2018, Kusano and Gabler, 2014, Li and Kockelman, 2016) and ADASs (Combs et al., 2019, Hendrickson and Harper, 2018, Li and Kockelman, 2016, Kusano and Gabler, 2014). The total number of preventable crashes was estimated in the target crash population methodology, and some studies stratified crashes based on severity level (Detwiller and Gabler, 2017, Hendrickson and Harper, 2018, Li and Kockelman, 2016, Kusano and Gabler, 2014). Table A1 in the appendix summarizes the target population studies.

4.3.2. Road Test Data Analysis

Analyzing AV testing on roads and crashes is one of the approaches used in the literature to evaluate AV safety. AV incident data were sourced from the California Department of Motor Vehicles (CA DMV) (Schoettle and Sivak, 2015, Teoh and Kidd, 2017, Favarò et al., 2017, Matysiak and Razin, 2018, Banerjee et al., 2018, Xu et al., 2019, Wang and Li, 2019, Petrović et al., 2020, Boggs et al., 2020), National Transportation Safety Board (NTSB) (Wang and Li, 2019), or AV manufacturers' self-reports (Schoettle and Sivak, 2015). CA DMV mandates that all manufacturers testing AVs on public roads file two different types of reports: (a) a report of a collision involving an AV within 10 days after the collision; and (b) an annual report summarizing the disengagements. In addition, conventional vehicle crashes were sourced from government agencies (Kalra and Paddock, 2016, Li and Zhai, 2019).

Three types of analyses were found in the literature. First, the rate of AV incidents was compared to conventional car incidents as a benchmark (Schoettle and Sivak, 2015, Teoh and Kidd, 2017, Matysiak and Razin, 2018, Banerjee et al., 2018, Favarò et al., 2017). The AV incident rate was estimated as either number of crashes per number of AV vehicle miles traveled (VMT) (Schoettle and Sivak, 2015, Teoh and Kidd, 2017, Favarò et al., 2017) or the number of disengagements per VMT (Matysiak and Razin, 2018, Banerjee et al., 2018). The AV incident rates were then compared to either conventional vehicle crash rates (Schoettle and Sivak, 2015, Teoh and Kidd, 2017, Favarò et al., 2017, Banerjee et al., 2018) or injury and fatality crash rates (Matysiak and Razin, 2018). Although AV crashes are reported by manufacturers, conventional vehicle crashes are reported by police, and therefore are underreported. To have a fair comparison between AVs and conventional vehicle crash rates, Toeh and Kidd (2017) used AV police-reportable crashes, and Schoettle and Sivak (2015) adjusted the conventional vehicle crash rates for underreporting. Given the disparities in the equivalence between AV and conventional vehicle crash rates, mixed conclusions were drawn in the literature regarding AV safety in terms of crash rates. Second, some studies investigated the characteristics of AV crashes in terms of collision type, location, speed, and cause. The majority of the literature ran a descriptive analysis of AV characteristics (Schoettle and Sivak, 2015, Favarò et al., 2017, Xu et al., 2019, Petrović et al., 2020), whereas some compared AV crash characteristics to conventional vehicle crashes (Schoettle and Sivak, 2015, Favarò et al., 2017, Petrović et al., 2020). Researchers found that the rate of rear-end crashes is higher in AV crashes (Schoettle and Sivak, 2015, Favarò et al., 2017, Petrović et al., 2020), while the severity of crashes is lower (Schoettle and Sivak, 2015). More rigorous statistical analyses, in the form of logistic regression (Wang and Li, 2019, Xu et al., 2019), decision tree (Wang and Li, 2019), and logit discrete choice models (Boggs et al., 2020), were used to uncover the factors contributing to AV crash risk (Boggs et al., 2020), collision type (Xu et al., 2019, Wang and Li, 2019), and severity (Xu et al., 2019, Wang and Li, 2019). Driving speed, on-street parking, speed limit, and collision location—highway, arterial and collector, and intersections—were shown to be associated with AV crash risk. The number of lanes marked centerline and clear weather conditions were shown to reduce the likelihood of AV crashes. AV driving mode (AV mode or conventional driver), collision location, roadside parking, rear-end collision, and one-way road were the main factors found to contribute to the severity level of AV-involved crashes. AV driving mode, AV stopped or not, vehicle turning movement, and whether crashes were associated with yielding to pedestrians/cyclists were the factors found to affect the collision type of AV crashes. The cause of AV disengagement was investigated by Banerjee et al. (2018), who found that 64% of disengagements were the result of problems in, or untimely decisions made by, the machine learning system.

Third, the safety reliability of AVs was examined by comparing the (a) AV failure rate to other safety-critical autonomous systems (Banerjee et al., 2018); (b) number of miles driven by AVs until a crash to the number of miles driven by conventional cars until a crash (Favarò et al., 2017); (c) number of failure-free miles AVs should drive to reach conventional cars' failure rates (Kalra and Paddock, 2016, Li and Zhai, 2019); (d) total number of miles driven to evaluate AV failure rate (Kalra and Paddock, 2016, Li and Zhai, 2019); and (e) total number of miles AVs need to drive to demonstrate their failure rate is statistically lower than that of conventional cars (Kalra and Paddock, 2016). Banerjee et al. (2018) compared AV reliability with other safety-critical autonomous systems in terms of reliability per mission and demonstrated that AVs are 4.22 times worse than airplanes and 2.5 times better than surgical robots. Favarò et al. (2017) estimated that AVs drive 500,000 miles before a crash, which shows the reliability of AVs versus conventional vehicles. However, estimations regarding the number of failure-free miles AVs should drive to reach conventional vehicles' failure rate resulted in higher thresholds of 1.6 million miles (Kalra and Paddock, 2016) and 140 million miles (Li and Zhai, 2019). Kalra and Puddok (2016) showed that AVs need to be driven 51 and 61 million miles to be able to test their failure rate and statistically examine their failure rate, respectively. However, much higher numbers (71 billion miles) have been estimated for AV testing requirements to be able to properly investigate AV safety (Kalra and Paddock, 2016). Table A2 summarizes the studies that used AV road test crashes to evaluate their safety.

4.3.3. Traffic Simulations

During the last decade, traffic simulation models have been implemented frequently to replicate the driving behavior of conventional vehicles (Young et al., 2014). Research studies have employed traffic simulation models to assess the safety effects of AVs and the assumption, methodologies, and limitations behind them (see Table A3 for a summary of related literature).

In the identified traffic simulation studies, various traffic microsimulation computer software was used, such as VISSIM (Kockelman et al., 2016, Katrakazas et al., 2019, Morando et al., 2018, Deluka Tibljaš et al., 2018, Rahman et al., 2019), MATLAB, SUMo, VENTOS, and PELOPS (Bahram et al., 2014, Arvin et al., 2018, Arvin et al., 2019, Qin and Wang, 2019). Depending on the study purpose, safety was evaluated at roadway segments (Katrakazas et al., 2019, Bahram et al., 2014, Ye and Yamamoto, 2019, Virdi et al., 2019, Qin and Wang, 2019, Zhang et al., 2015), intersections (Kockelman et al., 2016, Arvin et al., 2018, Arvin et al., 2019, Morando et al., 2018, Virdi et al., 2019, Rahman et al., 2019), roundabouts (Morando et al., 2018, Deluka Tibljaš et al., 2018), or on/off-ramps (Kockelman et al., 2016).

For developing the simulation scenarios, different car-following models were utilized for conventional vehicles and AVs. Various car-following models were implemented to replicate conventional vehicles' driving behavior, such as Wiedemann 74 (Arvin et al., 2018, Deluka Tibljaš et al., 2018, Virdi et al., 2019), Wiedemann 99 (Katrakazas et al., 2019, Morando et al., 2018, Zhang et al., 2015), and user-defined models (Ye and Yamamoto, 2019). For AVs, car following was in the form of modified built-in models, including modified Wiedemann models (Kockelman et al., 2016, Arvin et al., 2018, Morando et al., 2018, Deluka Tibljaš et al., 2018) or automated vehicle-specific models using external coding interfaces to either adjust a variable, introduce a new following strategy, or test various models (Bahram et al., 2014, Arvin et al., 2018, Ye and Yamamoto, 2019, Papadoulis et al., 2019, Virdi et al., 2019). In general, Wiedemann characterizes the car-following behavior by look-ahead distance, look-back distance, and average standstill distance, while modified Wiedemann 99 also considers headway time (PTV, 2018). Based on driving behaviors, various scenarios were developed to evaluate the impact of AVs on safety. The majority of the studies explored different AV MPRs as the main variable (Katrakazas et al., 2019, Bahram et al., 2014, Rahman et al., 2019, Arvin et al., 2018, Arvin et al., 2019, Morando et al., 2018, Deluka Tibljaš et al., 2018, Ye and Yamamoto, 2019, Papadoulis et al., 2019, Qin and Wang, 2019). Depending on the study, each simulation scenario was run multiple times to obtain reliable outputs for evaluating traffic safety. Since simulations do not lead to any crash, near-miss events were used instead to assess safety.

Surrogate safety measures (SSMs) were used to determine the number of near-miss events and, consequently, the associated level of traffic safety. The most commonly used SSMs in the studies were time-to-collision (TTC) and post-encroachment time (PET) (Kockelman et al., 2016, Katrakazas et al., 2019, Bahram et al., 2014, Arvin et al., 2018, Arvin et al., 2019, Morando et al., 2018, Deluka Tibljaš et al., 2018, Ye and Yamamoto, 2019, Papadoulis et al., 2019). Acceleration rate, velocity difference (Ye and Yamamoto, 2019), time-exposed time-to-collision (TET) (Bahram et al.), time-integrated time-to-collision (TIT) (Bahram et al., 2014, Qin and Wang, 2019, Zhang et al., 2015, Rahman et al., 2019), time-exposed rear-end crash risk index (TERCRI) (Zhang et al., 2015, Rahman et al., 2019), number of critical jerks (NCJ) (Rahman et al., 2019), and lane-change conflicts (Zhang et al., 2015) were the other types of SSMs used in these studies.

Most of the studies concluded that by increasing the AV MPR, the number of near-miss events decreased on segments (Bahram et al., 2014, Morando et al., 2018, Ye and Yamamoto, 2019, Qin and Wang, 2019), at intersections (Kockelman et al., 2016, Arvin et al., 2018, Arvin et al., 2019, Morando et al., 2018, Rahman et al., 2019), at priority intersections (Virdi et al., 2019), in bottlenecks, at on/off-ramps (Kockelman et al., 2016), and in roundabouts (Morando et al., 2018, Virdi et al., 2019). However, Deluka et al. (2018) indicated that an increase in the AV MPR in two roundabouts led to an increase in the number of conflicts. Moreover, Kockelman et al. (2016) showed an increase in conflicts by increasing the AV MPR at intersections. On the other hand, other studies showed that low AV MPRs were associated with a higher number of conflicts compared to zero MPR, but the number of conflicts decreased at intersections (Arvin et al., 2018, Virdi et al., 2019) and diverse diamond interchange (DDI) intersections (Virdi et al., 2019) by increasing the MPR in the simulation environment. Katrakazas (2019) also proposed a method to enable AVs to determine their trajectories to enhance safety in emergency situations. Study results indicated that the proposed method is capable of improving safety.

4.3.4. Driving Simulators

Probable challenges in human-vehicle interaction in the AV domain can take place in either the AV driver and AV interface stage (e.g., taking-over process) or the interaction between conventional vehicles and AVs (e.g., conventional vehicles entering the platoon of AVs). At different levels of automation, the AV driver needs to monitor or even intervene in the automation system to some extent in order to compensate for automation biases. On the other hand, AVs, at any MPR, will interact with conventional vehicles before they entirely dominate the future transportation system. In both cases, detailed knowledge of human driving behavior and reactions is necessary to evaluate AV safety. All the safety-related scenarios in reviewed studies could be categorized as (a) vehicle-human interaction (take-over situations in different driving states, such as drunk driving, drowsy driving, distracted driving, disengagement from the ADS, etc.) (Strand et al., 2014, Kundinger et al., 2018, Berthelon and Gineyt, 2014, Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015), or (b) vehicle-vehicle interaction (joining a conventional vehicle to a platoon of AVs) (Gouy et al., 2012, Lee et al., 2018). In both categories, a hazard scenario must be designed to determine the driver's performance in the evasive situation of interest. A hazard scenario is a situation that triggers the driver to make a maneuver and might be (a) a sudden blocked lane by another vehicle(s) (Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015), a sudden drift toward the edge of the road (Desmond et al., 1998), or a deceleration failure (Strand et al., 2014); or (b) safety challenges faced during driving, such as entering a platoon environment (Gouy et al., 2012, Lee et al., 2018) or controlling the vehicle while drowsy or drunk (Kundinger et al., 2018, Berthelon and Gineyt, 2014). The simulator experiments included three aspects—participants, experimental variables, and safety measurements—that had to be designed before the main experiment.

Different characteristics of participants used in designing simulator experiments included the following: age (Berthelon and Gineyt, 2014, Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015, Gouy et al., 2012, Strand et al., 2014, Lee et al., 2018, Kundinger et al., 2018, Desmond et al., 1998), gender (Happee et al., 2017, Gold et al., 2018, Blommer et al., 2015, Gouy et al., 2012, Strand et al., 2014, Lee et al., 2018, Kundinger et al., 2018, Berthelon and Gineyt, 2014, Desmond et al., 1998), annual mileage driven (Strand et al., 2014), driving experience (Strand et al., 2014, Gouy et al., 2012, Berthelon and Gineyt, 2014), previous experience with automated driving (Strand et al., 2014, Blommer et al., 2015), prior experience with a driving simulator (Gouy et al., 2012, Gold et al., 2018, Happee et al., 2017), and health condition (Kundinger et al., 2018, Berthelon and Gineyt, 2014). Each experiment took place in a controlled ODD and was based on a predefined procedure. Predesigned factors, such as (a) traffic density (Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015, Strand et al., 2014, Gouy et al., 2012, Lee et al., 2018, Kundinger et al., 2018, Berthelon and Gineyt, 2014), (b) MPR (Lee et al., 2018), (c) facility type (Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015, Strand et al., 2014, Gouy et al., 2012, Lee et al., 2018, Kundinger et al., 2018, Berthelon and Gineyt, 2014), and (d) repetition of experiment (Happee et al., 2017, Gold et al., 2018, Strand et al., 2014, Gouy et al., 2012, Desmond et al., 1998) and controlled factors—including the facility geometry design characteristics (Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015, Gouy et al., 2012, Lee et al., 2018, Berthelon and Gineyt, 2014) and speed (Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015, Strand et al., 2014, Gouy et al., 2012, Lee et al., 2018, Kundinger et al., 2018, Berthelon and Gineyt, 2014, Desmond et al., 1998)—were common experimental characteristics found in simulator studies. Some studies conducted only one experiment per participant to avoid learning effect bias (Blommer et al., 2015, Kundinger et al., 2018, Lee et al., 2018); others repeated the experiment to extract the maximum information from the available resources and tried to mitigate the learning effect bias by incorporating it as a variable in the model. However, almost all studies conducted a trial run before the main experiment to familiarize the participants with the simulator environment.

A metric is required to measure the performance of AVs and quantify the risks and benefits of AVs using simulator studies. To this end, SSMs were widely used as the response variable to quantify safety risks and benefits of AVs, namely take-over time (TOT) (Gold et al., 2018), TTC (Gold et al., 2018, Happee et al., 2017, Strand et al., 2014), brake application (Gold et al., 2018), crash/crash probability (Gold et al., 2018, Berthelon and Gineyt, 2014), steering response time (Happee et al., 2017, Lee et al., 2018), clearance toward the obstacle (Happee et al., 2017), road clearance metric (Happee et al., 2017), response time (Blommer et al., 2015, Strand et al., 2014), percent of time with eyes on the road (Blommer et al., 2015), steering magnitude (Lee et al., 2018), lateral control (Desmond et al., 1998), lane-change duration (Lee et al., 2018), Karolinska Sleepiness Scale (Kundinger et al., 2018), physical and perceptual fatigue (Desmond et al., 1998), average speed (Berthelon and Gineyt, 2014), and time headway (Strand et al., 2014, Gouy et al., 2012). The point of modeling different SSMs relates to the difference in their ability to capture near-crash events and critical maneuvers.

Finally, the SSMs were used to (a) find contributing factors to safety risk and benefits of AVs in different settings (Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015, Strand et al., 2014, Gouy et al., 2012, Lee et al., 2018, Berthelon and Gineyt, 2014), and (b) compare AV safety with conventional vehicle safety (Happee et al., 2017, Kundinger et al., 2018, Desmond et al., 1998). Linear regression (Gold et al., 2018), logistic regression (Lee et al., 2018), analysis of variance (ANOVA) (Blommer et al., 2015, Strand et al., 2014, Gouy et al., 2012, Lee et al., 2018, Berthelon and Gineyt, 2014), Fisher's exact test (Strand et al., 2014), analysis of covariance (ANCOVA) (Strand et al., 2014), and Cochran's Q test (Strand et al., 2014) were used to identify significant variables that influenced AV safety. Besides the participant characteristics and experiment characteristics (or elements) mentioned before, other variables—such as time budget (Gold et al., 2018, Happee et al., 2017), lanes driven (Gold et al., 2018, Happee et al., 2017), type of secondary tasks (Gold et al., 2018, Happee et al., 2017, Blommer et al., 2015), automation level (Strand et al., 2014), extent of hazard scenario and challenges (e.g., moderate/severe/complete deceleration failure, or different time headway within the platoon) (Strand et al., 2014, Gouy et al., 2012), platoon size (Lee et al., 2018), and alcohol concentration (Berthelon and Gineyt, 2014)—were considered. Results showed that take-over scenarios, traffic density, experiment repetition, and defined time budget were highly influential factors affecting SSMs (Gold et al., 2018). In addition, scheduled disengagement (Blommer et al., 2015), lower automation levels, and lower extent of hazard scenarios (Strand et al., 2014) led to better performance of drivers during the take-over situation. Drunk driving affected the longitudinal and lateral control of the vehicle and driver reaction to evasive maneuver (Berthelon and Gineyt, 2014). Moreover, in the platoon environment, the higher MPR (Lee et al., 2018) and lower time headway of AVs resulted in more aggressive driving behavior from conventional vehicles joining the platoon. Furthermore, drunk driving most likely impaired lateral and longitudinal control of AVs in lower levels of automation (Berthelon and Gineyt, 2014). To compare conventional vehicles and AVs in terms of safety risks and benefits, ANOVA (Kundinger et al., 2018, Desmond et al., 1998) and Fisher's exact test (Happee et al., 2017) were commonly used. Results showed that automated driving would negatively affect a take-over scenario in response to a risk while the vehicle is disengaged from the ADS (Happee et al., 2017) (Desmond et al., 1998) and increase driver drowsiness (Kundinger et al., 2018) compared to manual driving.

More details on the reviewed driving simulator studies can be found in Table A4.

4.3.5. System Failure Risk Assessment

System operation failure is one probable risk that AVs encounter (Koopman and Wagner, 2016). Malfunctioning sensors in detecting objects (pedestrians, bikes and cyclists, vehicles, obstacles, etc.), misinterpretation of data, and poorly executed responses can jeopardize the reliability of AVs and have serious safety consequences in an automated environment (Bila et al., 2017). The failure rate of each component of AVs was synthesized by Bhavsar et al. (2017). To this end, each component of the ADS and ADAS was examined individually, and the failure rate was determined for each component based on the evidence from the existing literature. The researchers developed a hierarchical model to synthesize AV failure risks associated with the vehicle and infrastructure. The failure risks of the communication system, hardware system (sensor and integration platform failure), and software system were ranked the highest, with 9.5%, 4.2%, and 1.0% failure probability, respectively. The failure probability of an AV involved in a crash with a non-AV was also calculated by multiplying the risk of failure of AVs and the crash probability of conventional vehicles.

4.3.6. AV Safety Effectiveness

AV safety effectiveness can be defined using AV SSMs and crash rates. For example, the safety effectiveness of AVs can be estimated as follows:

$$\text{Safety Effectiveness} = 1 - \frac{\text{AVs}'\text{crash rate}}{\text{Conventional vehicles}'\text{ crash rate}} \quad (1)$$

However, decisions about AV safety effectiveness or the validity of AV safety cannot be based on the results of a single study because results typically vary from one study to the next. Rather, a mechanism is needed to synthesize data across studies. Wang et al. (2020) synthesized the results of previous simulation and field experiments that estimated safety effectiveness by performing a meta-analysis of 89 studies. They estimated the safety effectiveness of nine ADASs, in descending order: intersection movement assist, pedestrian collision and mitigate (PCAM), lane-departure warning (LDW), lane-change warning (LCW), forward collision warning (FCW), electronic stability control (ESC), blind-spot warning, automated emergency braking (AEB), and adaptive cruise control (ACC).

Wang et al. (2020) further designed a target crash population study to implement the estimated ADASs' safety effectiveness rates and quantify the potential impacts of CVs and AVs on different crash types. The results of their analyses showed that 3.4 million crashes could be prevented between 2012 to 2016; this figure represented a significant reduction in crashes in India (54.24%), Australia (51.55%), the United States (48.07%), New Zealand (45.36%), Canada (44.71%), and the UK (40.95%).

5. Discussion

5.1. Evaluating AV Safety Quantification Approaches

Six approaches for quantifying AV safety were identified in this study. The identified approaches were investigated in terms of their input, their output, and the level of safety implications for which they can be used. The inputs of the approaches used in the literature included predefined information on AVs' functionality, observed conventional vehicle crashes, AV road test crashes, errors, study-specific observations, assumptions, and speculations regarding AV implementation. The review showed that a target crash population approach can be used to estimate the number of preventable crashes for transportation system and society-level evaluations. Road test data analysis, which extracts the characteristics of crashes and safety issues AVs can encounter and their frequencies, can be used for evaluating AV safety at the transportation system and society levels. Moreover, driving simulator and traffic simulation studies can be used for evaluating AV safety in terms of SSMs under different implementation scenarios. While driving simulators investigate AV safety and its potential operational challenges (e.g., disengagement) at the vehicle level, traffic simulation studies consider AV performance and interactions with other vehicles in a fleet. The safety effectiveness of AVs is statistically estimated using the outputs of driving simulators and simulation studies. Although safety effectiveness was defined for ADASs in the literature, this method can be used for evaluating higher levels of ADS safety as well. The estimated safety effectiveness (from traffic simulations or driving simulators) can be used for both transportation-system-level and society-level evaluations. Finally, the system failure assessment approach can be used to evaluate the vehicle-level safety of AVs in terms of the system components' failure rate. Figure 4 summarizes the inputs, outputs, and potential application of the approaches.

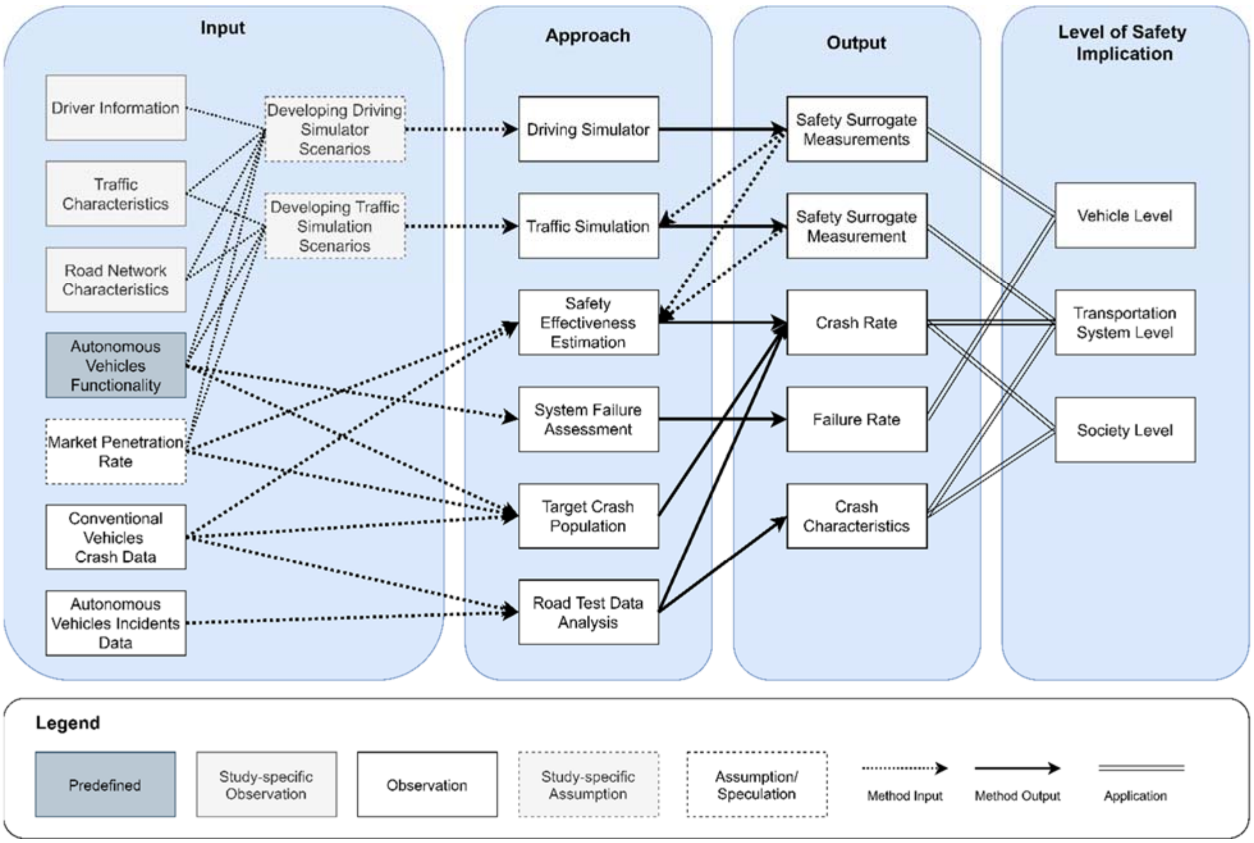

Figure 4. Summary of the inputs, outputs, and potential application of AV safety quantification methodologies

Based on the findings of this review, the AV safety quantification approaches vary in terms of (a) availability of input data, (b) suitability for evaluating different levels of automation, and (c) reliability of estimations. Thus, we qualitatively and relatively evaluated each approach using these three criteria (Figure 5). The road test crash data analysis method is able to evaluate the safety of higher levels of automation with minimal uncertainty; however, it requires extensive and reliable AV crash data. The target population crash method needs minimum input data and can estimate the safety benefits of lower levels of automation, but considerable uncertainty exists in the estimates. The traffic simulation, driving simulator, safety effectiveness, and system failure risk assessment approaches can be used for evaluating all levels of automation. However, the safety effectiveness and system failure risk assessment methods require fewer input data than the others.

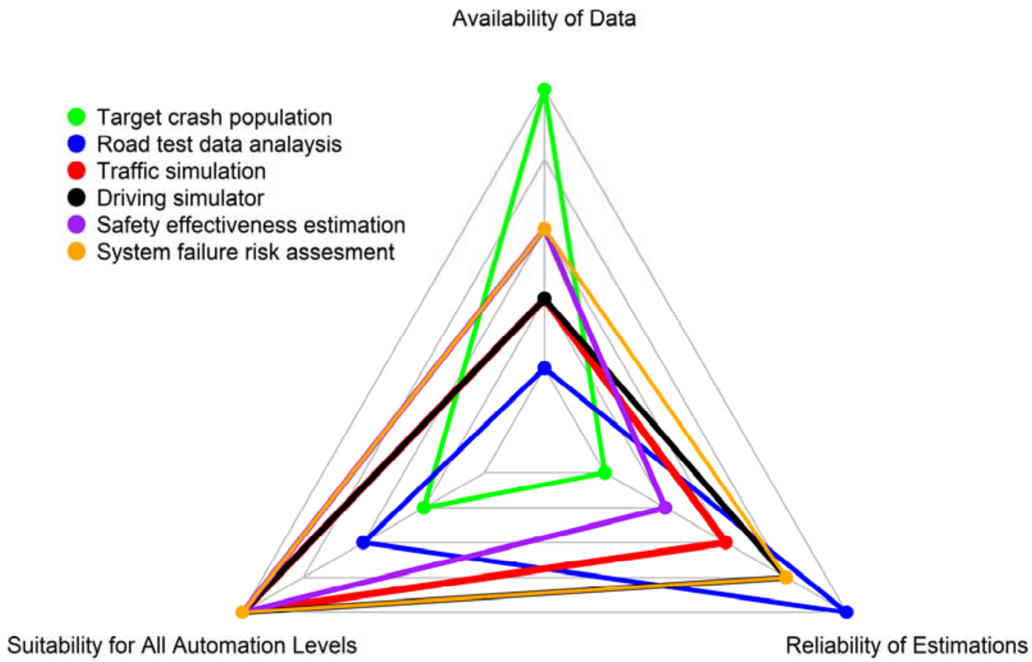

Figure 5. Trade-offs between availability of data, suitability for evaluating levels of automation, and reliability of estimations

Note that we did not evaluate the existing results of the quantification approaches but rather represent their potential applicability for future AV safety validations.

5.2. AV Safety Validation Challenges

AV safety needs to be fully validated before making any decisions about implementing AVs. We identified four challenges to AV safety validation:

1. Limitations in the existing quantification methodologies.
2. Uncertainties in AV implementations and their impacts on AV safety.
3. Potential riskier behaviors of AV passengers as well as other road users.
4. New safety issues related to AV implementations.

5.2.1. Limitation in the Existing Quantification Methodologies

Certain limitations in existing AV safety quantification methodologies jeopardize the safety validation of this new technology. The target crash population studies did not account for the scenarios that AVs might cause (e.g., disengagement or system failure) and totally disregarded probable new crashes. In addition, the mixed traffic safety issues (interaction of AVs and conventional vehicles) and driver reaction to hazards were not considered in the target crash population methodology. Thus, this method is expected to represent a theoretical upper bound (or optimistic scenarios) of the potential safety benefits of AVs, not their expected actual benefits.

On the other hand, driving simulator studies were designed to evaluate AVs' potential safety challenges. Traffic simulation studies can also be used to account for both AV and conventional vehicles' driving behaviors and mixed traffic safety issues. Driving simulator and traffic simulation study results, however, are subject to biases from a variety of sources, such as participants (e.g., driving behavior, fatigue, etc.), simulator and simulation environment (physical fidelity, functional fidelity, etc.), and SSM selection. Different SSMs were employed for evaluating AV safety in simulators and simulations. Although a general comparison in terms of the overall safety trend of AVs could be conducted using SSMs, the results from the literature cannot be compared directly. Another challenge in simulator and simulation studies is the limitations in calibration and validation of experiment results since AV road tests are limited.

The system failure risk assessment methodology was used to investigate the failure probability of ADASs/ADSs and to quantify the failure rate of AVs. However, looking at the system failure rates individually can result in overestimating AV failure because other components can compensate for the failure of the deficient components. For example, in the event of an AV radar malfunction, the camera vision can help to activate the collision prevention system and avoid a collision. Moreover, the system failure assessment relies on the system failure rates from private companies. Collecting accurate system failure rates is challenging since this information should be collected from the manufacturer and might be underreported. Given that safety effectiveness estimations are based on the results of simulation and simulator studies, they carry remarkable uncertainty as well.

The road test data analysis was purported to be the most reliable method for validating AV safety. However, existing road tests are limited, and more data are required to draw a reliable conclusion on AV safety. Recent increases in AV road test analysis studies (Figure 3) can be associated with larger and more reliable road test datasets. However, validating AV safety with road tests has been criticized because they expose road users to road hazards (Kalra, 2017).

5.2.2. Uncertainties in AV Implementations and Their Impacts on AV Safety

AV impacts on transportation go beyond safety impacts. By offering a safer, cheaper, and more comfortable travel option to individuals with disabilities, AVs may induce additional transportation demand and encourage longer trips. AVs can also encourage shifting from public transit and active transportation (walking and cycling) to private cars (Fagnant and Kockelman, 2015). Transportation and land use are tightly linked in urban areas (Rodrigue et al., 2016), so changes in transportation can ultimately result in urban sprawl (i.e., migrating to areas with lower density and consequently spreading a city's boundaries). Urban sprawl increases total VMT (Childress et al., 2015) and negatively influences accessibility in an urban area (Milakis et al., 2017). In addition, the uncertainties in intentions for use of AVs and disproportionate ownerships will affect transportation systems, travel patterns, and urban design. VMT changes, pedestrian and bike traffic variations, and modal shift are factors that can impact traffic safety at the transportation system and society level. Therefore, they should be considered in AV safety validations. Full-chain assessment of AV safety is required to address the impacts of AV implementations on the transportation system, travel patterns, and urban design and to translate these changes into safety implications.

5.2.3. The Potential Risk Behaviors of AV Passengers and Other Road Users

Changes in the behaviors of AV and conventional vehicle drivers need to be considered in AV safety validations. Based on research by AAA Foundation, a substantial minority of early adopters of braking assistance systems reported having had a crash or near-crash while driving a vehicle without this technology, supposedly because of incorrect expectations from the unequipped vehicle to provide warnings (Jenness et al., 2007). Gouy et al. (2012) ran a driving simulator experiment and showed that the conventional vehicles would be driven more aggressively if joining a platoon of AVs. The riskier behavior of drivers during interaction with AVs can be explained by the *risk homeostasis hypothesis* (Wilde, 1998). Based on this hypothesis, every person has an acceptable amount of risk that they find tolerable. According to Wilde (1998), "If the perceived level of risk in one part of a person's life changes, they will compensate by either reducing or increasing the risks they take—all in order to maintain an equilibrium of perceived risk."

5.2.4. New Safety Issues Related to AV Implementations

Cybersecurity is another potential concern related to AVs because hacking and misuse of vehicles can result in catastrophic crashes (Lee, 2017, Taeihagh and Lim, 2018, Cui et al., 2019). A car hacking experiment conducted by (Jafarnejad et al., 2015) demonstrated that electric vehicles could be easily controlled remotely by mobile applications that forced the vehicles to go forward or backward, limited their speed, and so on. In addition, the ethical dilemma associated with AV reactions during unavoidable situations introduces another challenge in AV operation (Goodall, 2014, Awad et al., 2018) that requires further attention. Although the ethical issues of AVs cannot directly impact AV safety validation, they concern the liability of AVs in crashes, which requires judiciary attention.

5.3. Gaps and Limitations

This review has certain limitations. First, the focus of this study was on AV safety quantification methods; therefore, we did not include the literature that evaluated ADAS safety implications or proposed frameworks and conceptual models for AV safety evaluation rather than quantifying the impacts. Both ADAS safety evaluation methods and proposed frameworks for AV safety evaluation might have the potential to address some of the limitations of the existing quantification methods. Second, we examined the AV safety evaluation methodologies qualitatively and relatively. Future research can quantify the inherited uncertainties in each method and provide a more accurate comparison between the methods.

Third, we focused on methodologies that quantified the substantive safety of AVs rather than the nominal safety and perceived safety. However, the safety of vehicles should be validated based on three definitions of safety. For example, even though AV safety can be comparable to that of conventional vehicles, the degrading perception of AV safety by users may hinder the adoption of this new technology. Future research is required to review the literature and examine the methodologies used for evaluating AV nominal safety and perceived safety for more accurate validation and understanding of AV safety.

6. Summary and Conclusions

In this study, we identified six methodologies that were used for quantifying AV safety implications. The quantification methodologies were compared in terms of their input and output, levels of safety implication evaluations (vehicle level, transportation level, and society level), availability of input data, capability to evaluate different levels of automation, and reliability of estimations. This comparison can be used as a guideline for future research when choosing the appropriate AV safety evaluation method based on the study objective and limitations. The existing methodologies for AV safety evaluation carry certain shortcomings and cannot be used for fully validating AV safety. More research is required to understand and evaluate AV safety and address the gaps in the existing methods. As more miles are driven by AVs on the roads, we expect more AV crash data that can help researchers to validate AV safety. Future research is also needed to address the challenges in AV safety validation. Particularly, regulations and policies are required to allow AV road tests while ensuring road user safety. Full-chain assessment of AV safety can augment the discussion about the safety implications of this new technology for further investments, policy evaluation, and public awareness. Finally, future research is warranted to examine the risk homeostasis hypothesis within the context of AVs and emerging safety issues related to AV implementations.

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Credit Author Statement

Soheil Sohrabi: conceptualization, methodology, literature review, investigation, visualization, writing—original draft, writing—reviewing and editing, supervision. **Ali Khodadadi**: literature review, investigation, writing—original draft. **Seyedeh Maryam Mousavi**: literature review, writing—original draft. **Bahar Dadashova**: validation, writing—reviewing and editing, supervision. **Dominique Lord**: validation, writing—reviewing and editing, supervision.

Appendix

Tables A1 to A4.

Table A1. Summary of target crash population studies

Author	ADS/ADAS	Target Crashes	ODD						Significant Results
			Road Type	Road Surface Condition	Weather Condition	Lighting Condition	Speed	Effectiveness	
Agriesti et al. (2019)	Level 3	Distracted driving, insufficient safety distance, speeding, skidding, road departure	Highways	✓	✓	✓	✓	100%	• 66% of crashes involving AVs and 6.6% of crashes involving conventional vehicles (considering 10% MPR) could be avoided.
Combs et al. (2019)	Pedestrian detection	Transportation-related pedestrian crashes	Urban/rural, intersection/not intersection, freeway/not freeway	NA	NA	NA	✓	100% except for adverse condition (20%)	• Different combinations of sensors can lead to a 30% to 90% reduction of fatal pedestrian crashes.
Lubbe et al. (2018)	AEB, LCW, LKA*, ESC	30 pre-crash scenarios	NA	✓	✓	NA	✓	100%	• Fatality reduction from 12–13% (using passive safety systems only) to 45–63% (using advanced ADAS and assuming cautious driving). • Reduction of vulnerable road user fatalities by 33–41%.
Detwiller and Gabler (2017)	AEB	Transportation-related pedestrian crashes	Urban area	NA	NA	NA	✓	100%	• Employing two different sets of rules resulted in a reduction or mitigation of 40% and 95% of crashes, respectively.
Yanagisawa and Rau (2017)	Level 2 to Level 4	37 pre-crash scenarios	Intersection, ramp, highway, work zone	✓	✓	✓	✓	100%	• L2 to L4 can address 35–250 billion dollars in comprehensive costs and 1100–11,000 fatal crashes annually.
Hendrickson and Harper (2018)	BSM, LDW, and FCW	Lane-change crashes, lane-departure crashes, and rear-end collision	NA	NA	NA	NA	✓	100%	• All technologies together can mitigate 1.3 million crashes annually, including 133,000 injury and 10,000 fatal crashes.
Lee and Kockelman (2016)	CACC, LKA, ESC	37 pre-crash scenarios	NA	NA	NA	NA	NA	NA	• Reduction of crash costs by 126 million annually. • Reduction of functional human-years lost by nearly 2 million (per year).
Kusano and Gabler (2014)	FCW, PCAM, LDW	18 pre-crash scenarios	NA	NA	NA	NA	NA	NA	• Safety systems can mitigate 20% and 26% of serious injury and fatal crashes, respectively.

Note: NA = Not Applicable.
* LKA: Lane Keeping Assistant

Table A2. Summary of AV road test data analysis studies

Study	Type of Analysis	Data Source	Approach	Significant Results
Schoettle and Sivak (2015)	Frequency; characteristics of the incident	CA DMV (2014–2015) and Google self-report (2012–2014) (11 crashes)	• Comparing AV and conventional cars' crash rates after adjusting for underreporting. • Descriptive analysis of crash characteristics (vehicle motion at the time of the crash, crash type, and crash severity) and comparison to conventional vehicles.	• Most of the crashes happened while the AV's speed was less than 5 mph. • The rate of rear-end crashes in AVs is higher than conventional cars. • The severity of AV crashes is lower than conventional cars. • The rate of AV crashes is 8 times higher than conventional vehicles.
Kalra and Paddok (2016)	Reliability	Accident rates in the US (2013)	• Estimating number of failure-free miles AVs should drive to reach conventional cars' failure rate using survival analysis. • Estimating the required total number of miles driven to evaluate AVs' failure rate. • Estimating the total number of miles AVs need to drive to demonstrate their failure rate is statistically lower than conventional cars.	• AVs need to drive 1.6 million miles failure-free to be as safe as conventional cars. • AVs need to drive 51 and 61 million miles to be able to test their failure rate and statistically examine if their failure rate is lower than conventional cars, respectively.
(Teoh and Kidd, 2017)	Frequency	CA DMV (2009–2015)*	• Comparing AV (police-reportable) crash rate to conventional cars' crash rate.	• Google self-driving cars are safer than conventional human-driven passenger vehicles (2.19 vs. 6.06 per million VMT).
Favarò et al. (2017)	Frequency; characteristics of the incident; reliability	CA DMV (September 2014 to March 2017) (5326 disengagements and 26 accidents)	• Descriptive analyses of crashes by collision type, location, and manufacturer. • Comparing AV crash rate and number of miles driving until an accident to conventional cars' crash rate and number of miles driving until an accident.	• The rate of crashes was lower for AVs than conventional cars, and AVs will drive longer before an accident (~42,000 vs. 500,000 miles). • Most of the AV crashes happened at intersections. • Rear-end crashes are higher for AVs than for conventional cars.
Matysiak and Razin (2018)	Frequency	CA DMV (2015–2017)	• Comparing AVs' disengagement data to injury and fatal crashes in Europe and US.	• AVs' crash rate is 2 to 3 times higher than conventional cars. • AVs should drive more than 442 million km fatal-free to be considered safer than human-driven cars.
Banerjee et al. (2018)	Frequency; characteristics of the incident; reliability	CA DMV (September 2015 to November 2017)	• Comparing AVs' disengagement rate to conventional cars' accident rates. • Analyzing the cause of disengagement from manufacturer report (after excluding unknown causes). • Comparing to other safety-critical autonomous systems.	• Conventional vehicles were 15−4000 times less likely (depending on the AV manufacturer) than AVs to have an accident. • 64% of disengagements were the result of problems in, or untimely decisions made by, the machine learning system. • In terms of reliability per mission, AVs are 4.22 times worse than airplanes and 2.5 times better than surgical robots.
Xu et al. (2019)	Characteristics of the incident	CA DMV (January 2015 and June 2018)	• Using bootstrap-based binary logistic regressions to investigate the factors contributing to the collision type and severity of CAV-involved crashes.	• Rear-end and sideswipe crashes are the two predominant collision types, which account for 57.5% and 28.8% of CAV-involved crashes, respectively. • AV driving mode, collision location, roadside parking, rear-end collision, and one-way road are the main factors contributing to the severity level of CAV-involved crashes. • CAV driving mode, CAV stopped or not, CAV turning or not, normal vehicle turning or not, and normal vehicle overtaking or not are the factors affecting the collision type of CAV-involved crashes.
Wang and Li (2019)	Characteristics of the incident	CA DMV (2017 to 2018) (107 crashes) NTSB (2017 to 2018) (6 crashes)	• Investigating the factors contributing to AV crash collision types and severity using logistic regression and decision tree.	• The highway and automated driving mode were identified as the location where severe injuries are likely to happen due to high travel speed. • Collision types of AV-related crashes depend upon the driving mode, location, and whether crashes are associated with yielding to pedestrians/cyclists. • Both ordinal logistic regression and the decision tree models show consistent results.
Xu et al. (2019)	Characteristics of the incident	CA DMV (January 2015 and June 2018) (72 crashes)	• Descriptive statistics analysis to investigate the characteristics of AV-involved crashes. • Binary logistic regressions were developed to investigate the factors contributing to the collision type and severity of AV-involved crashes.	• AV driving mode, collision location, roadside parking, rear-end collision, and one-way road are the main factors contributing to the severity level of AV-involved crashes. • AV driving mode, AV stopped or not, AV turning or not, normal vehicle turning or not, and normal vehicle overtaking or not are the factors affecting the collision type of AV-involved crashes.
Li and Zhai (2019)	Reliability	The accident rate on China highways (2008–2015)	• Finding the minimum fault-free distance of AVs to be as safe as conventional cars by inferring the overall distribution from the sample distribution and calculating how much sample size is needed at minimum.	• With a 95% confidence interval, AVs need to drive fault-free for ~226 million km and should be tested for 115,972 million km to be considered as safe as conventional cars.
Petrović et al. (2020)	Characteristics of the incident	CA DMV (2015–2017) (53 accidents)	• Analyzing the type of collision frequencies using descriptive statistics of crash data.	• The rear-end type of collision is statistically more significantly frequent in traffic accidents with AVs.
Boggs et al. (2020)	Characteristics of the incident	CA DMV (2014–2018) (113 crashes)	• Friquintis and Bayesian binary logit model to examine the factors contributing to the AV crashes.	• Speed of conventional vehicle, missing speed, on-street parking, speed limit, driving through arterial and collector, and intersections were positively associated with AV crash assurance. • The number of lanes marked with a centerline and clear weather conditions increase the risk of crashes.

* Only Google self-driving car crashes.

Table A3. Summary of traffic simulation studies

Authors	Simulation Information					Driving Behavior Model		SSM	Results
	Facility Type	Length	Software	Technology	MPR	Conventional Vehicle	AV		
Kockelman et al. (*10*)	• Intersection • Freeway on/off-ramp	NA	VISSIM	AV	25%, 50%, 75%, and 100%	NA	NA	TTC	• Bottleneck: 40–88% reduction in the number of conflicts by increasing the AV MPR from 0% to 100%. • 4-leg intersection: 4% reduction in the number of conflicts by increasing the AV MPR from 0% to 100%. • 77% and 31% reduction in the number of conflicts for two other intersections. • 17% increase for another intersection. • Freeway on-ramps/off-ramps: 49% reduction in the conflicts by increasing the MPR from 0% to 100.

Katrakazas et al. (*11*)	A section of highway	4.52 km	VISSIM	AV	NA	Wiedemann 99	NA	TTC	• The artificial and the real-world datasets indicated that:
									  ◦ If the network-level, real-time collision risk indicates a situation as conflict-prone traffic, the probability of detecting if a vehicle poses a threat to an AV increases by 10%.
									  ◦ When traffic conditions were marked as safe, the prediction did not improve the probability of a road user being a threat for the ego-vehicle.
									• By using disaggregated traffic data (i.e., 30 seconds), the probability of a traffic participant posing a threat to the ego-vehicle was enhanced by about 6%.
									• The proposed method allows AVs to change their trajectory, reduce their speeds, or even prompt a passenger to take the controls to ensure safety even when other sensor systems fail since network-level predictions utilize data at a higher temporal interval than the sampling frequency.

Deluka et al. (*16*)	Roundabout	NA	VISSIM	AV	0%, 10%, 25%, and 50%	Wiedemann 74	Calibrated Wiedemann 74	TTC and PET	• By increasing the AV MPR from 0% to 50%:
									  ◦ Omisalj roundabout: number of conflicts increased from 0 to 45; the majority of them were rear-end conflicts.
									  ◦ Malinska roundabout: the conflicts increased from 2 to 5, with all the conflicts being rear-end.

Morando et al. (*15*)	• Signalized intersection • Roundabout	NA	VISSIM	AV Level 4	0%, 25%, 50%, 75%, and 100%	Wiedemann 99 car-following model with default parameters	Modified Wiedemann 99	TTC	• Intersection: AVs reduced the number of conflicts by 20% to 65%, with an AV MPR of between 50% and 100%. • Roundabout: the number of conflicts was reduced by 29% to 64% with 100% AV penetration rate.
Arvin et al. (*13*)	Intersection	NA	SUMO	AV Levels 3 and 5	0%, 7%, 15%, 40%, 60%, 80%, and 100% (for MPR 100, different combinations of AV Level 3 and AV Level 5 were used)	Wiedemann 74	Modified Wiedemann 74	TTC	• Cases with human-driven vehicles, Level 3 and Level 5 AVs: the average crashes decreased from 9 to 0 by increasing the MPR from 0% to 100%. • Cases with AV Level 5 and human-driven vehicles: at low AV MPR (below 40%), the number of crashes increased from 9 to 10. • Cases with AV Level 5 and human-driven vehicles: by increasing the AV MPR (over 40%), the number of crashes reduced from 10 to 0.
Arvin et al. (*14*)	Intersection	NA	VENTOS	Highly automated vehicles (HAVs) and low-level AVs (LAVs)	Various combinations of conventional vehicles, LAVs, and HAVs	ACC model	Wiedemann	• TTC • Driving volatility	• For AV MPR of 0%, an average of 9.43 conflicts was observed. • At AV MPR of 100%, there was a 90.1% improvement compared to the baseline. • Where all the vehicles were HAVs: the intersection became conflict-free. • By increasing the MPR of LAVs and HAVs, the volatility decreased from 8.5 to 5.5 for acceleration.

									• By increasing the MPR of LAVs and HAVs, the speed volatility decreased from 6.9 to 3.8.
Bahram et al. (*12*)	Four-lane highway	6000 m	PELOPS	HAV	0%, 50%, and 100%		The model of HAV controller developed in Simulink; the model is coupled via Xface2 to the interface in PELOPS	• TTC • TET (lower values represent safer situations) • TIT (lower values are associated with higher level of safety)	• TTC = 3.0 sec: 1440, 729, and 16 conflicts for MPRs of 0%, 50%, and 100%, respectively. • At 50% MPR of HAV, the critical situation < 1.5 sec increased remarkably compared to the base scenario. • MPRs of 0%, 50%, and 100% are associated with the TET of 144.1 sec to 72.9 sec and 1.6 sec, respectively. • By increasing the MPR from 0% to 50% and 100%, the TIT changed from 66 to 76.29 and 1.10 sec^2, respectively. • MPR of 50% is not as safe of the other cases since AVs tend to follow other vehicles closely.

Virdi et al. (*20*)	Intersection	NA	VISSIM	CAV	0% to 100% (10% incremental)	Wiedemann 74 and Wiedemann 99	Virdi CAV control protocol algorithm	• TTC
								• PET
									• The first 20% MPR of CAVs resulted in:
									  ◦ +22% change in conflicts at signalized intersections.
									  ◦ 87% reduction in conflicts at priority intersections.
									  ◦ −62% change in conflicts at roundabouts.
									  ◦ 33% increase in conflicts at DDI intersections.
									• At high CAV MPR, a global reduction in conflicts occurred such that the 90% CAV MPR was accompanied by:
									  ◦ −48% change in conflicts at signalized intersections.
									  ◦ 100% reduction in near-miss events at priority intersections.
									  ◦ −98% change in near-crash events at roundabouts.
									  ◦ 81% reduction in conflicts at DDI intersection.

Zhang et al. (*21*)	Four-lane freeway	7 km	VISSIM	CAV	0%, 10%, 20%, and 30%	Wiedemann 99	Car-following and lateral lane-change decisions coded in C++	• TET
								• TIT
								• TERCRI
								• LCC
									• Compared to the base scenario:
									  ◦ Providing 1 or 2 exclusive lanes led from −1.8% to −87.1% and −2.1% to −85.3% of lateral conflicts.
									  ◦ Installing 1 or 2 exclusive lanes resulted in +42.4% to −52.90% and +45.7% to −55.2% of longitudinal risk.
									    o Only MPRs of 10% and demands < 6000 veh/h providing exclusive lanes had mainly adverse effects on longitudinal conflicts ranging from 1.8 to −40.4, but for other scenarios with different MPRs and traffic demands, the overall safety improved.

Rahman et al. (*22*)	• Arterial segment
	• Intersection
		3.8 miles	VISSIM	CV and CV lower-level automation (CVLLA) (two automated features such as automated braking and lane-keeping assistance)	0%, 40%, 60%, 80%, and 100%	Wiedemann	C++ programming	• TTC
								• TET
								• TIT
								• TERCRI
								• LCC
								• NCJ
									• Segment: by increasing the MPR from 0% to 100%:
									  ◦ TET decreases from approximately 1750 to 1450 and 1370 for CV and CVLLA, respectively.
									  ◦ TIT decreases from 445 to 345 and 310 for CV and CVLLA, respectively.
									  ◦ TERCRI reduces from 390 to 308 and 265 for CV and CVLLA, respectively.
									  ◦ LCC decreases from 520 to 455 and 405 for CV and CVLLA, respectively.
									• Intersection: for different evaluated values of TTC and PET thresholds:
									  ◦ Total number of conflicts were decreased by 21–24% for CV technologies compared to base scenario.

									• Total number of conflicts were reduced by 31–34% for CVLLA compared with that of base condition.
Ye and Yamamoto (*17*)	Two-lane road segment	10 km	NA	CAV	10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%	User-defined	User-defined	• TTC • Acceleration rate • Velocity difference	• Reduction in the number of dangerous situations by increasing the MPR depends on traffic density and TTC. • By increasing the MPR from 0% to 100%, the reduction in the dangerous situations falls within 0% and 97%.
Papadoulis et al. (*18*)	Three-lane motorway section	4.27 km	PTV VISSIM 9.0 and API	CAV	0%, 25%, 50%, 75%, and 100%	Wiedmann 99	External CAV driver model API written in C++	• TTC • PET	• Reduction in conflicts by 12–47%, 50–80%, 82–92%, and 90–94% for MPRs of 25%, 50%, 75%, and 100%, respectively.
Qin and Wang (*19*)	Freeway	20 km	MATLAB	CAV	Different MPRs	NA	NA	• TET • TIT	• Average reduction of 75% to 95% depending on the number of feedback links by increasing the CAV MPR. • By increasing the feedback links from 1 to 2, average reduction in collision risks changes from 75% to 95%. • There is not a significant reduction in the number of conflicts between 2, 3, and 4 links.

Note: NA = Not Applicable.

Table A4. Summary of driving simulator studies

Author	Participants' Information			Experiment Factors				AV Challenge	Scenario Parameters	Statistical Tool	Response Variable	Significant Results
	Age	Annual mileage	Driving experience	Facility	Speed	Traffic	Repetition					
Gold et al.[*] (2018)	19–79	✗	At least 1 year of driving experience	Three-lane highways	120 km/h	0, 10, 20, 30 veh/km	✓	Disengagement	Time budget, lane driven, traffic density, secondary tasks, repetition of the experiment	Generalized linear regression	TOT, TTC, crash, brake application	• Traffic density (negatively), repetition (positively), and time budget were highly influential. • TOT, TTC, and crash probability showed reliable results.
Happee et al. (2017)	33.5 (SD = 9)	✗	Familiarity with the driving simulator	Three-lane highways	120 km/h	With (30 veh/km)/ Without traffic	✓	Disengagement	Time budget, lane driven, traffic density, secondary tasks	Linear regression, Fisher's exact tests	In total, 19 performance metrics in terms of risk, braking, and steering, such as TTC, clearance toward the obstacle and the roadside, peak accelerations, overshoot, etc.	• AV can cause delayed initial steering and braking, lower TTC, and stronger braking or steering. • No difference between cognitive and visual distraction. • The precision of maneuver remained unaffected.
Blommer et al. (2015)	40 (24 < 45 yr and 16 > 45 yr)	✗	No experience of automated driving	Four-lane undivided roadway	50–70 mph	Light traffic	✗	Disengagement	Continuous and scheduled automated driving, secondary tasks	ANOVA	Response time, eye glance behavior, percent eyes-on-road time	• Radio listeners responded significantly faster. • The scheduled driver engagement strategy performed better when visual distraction was used.
Strand et al. (2014)	24–65	>10,000 km	No automated driving experience & > 5 yr driving experience	Two-lane undivided rural road	70 km/h	✓	✓	System failures	Automation level, extent of system failure (moderate/ severe/completely)	ANOVA, ANCOVA, Fisher's exact tests	Minimum TTC, minimum time headway, response time, point-of-no-return, number of collisions	• Further automation leads to lower performance of driver. • Drivers performed better at controlling the lower extent of system failure.
Gouy et al. (2012)	20–63	2000–56,000 km	Experience with a driving simulator, at least 1 year of driving experience	Three-lane highway	90 km/h	✓	✓	Platoon environment	Time headway within the platoons	ANOVA	Time headway	• Smaller average and minimum time headway when driving adjacent to AV platoons with short time headway.
Lee et al. (2018)	23 below and 7 above 50 years of age	✗	Not considered	Three-lane highway	100 km/h	✓	✗	Platoon environment	Platoon size, different MPR	ANOVA, logistic regression	Steering magnitude, steering velocity, lane-change duration, lane-change (success/failure)	• Smaller average and minimum time headway when driving adjacent to AV platoons with short time headway.
Kundiger et al. (2018)	18–64	✗	Not considered	Three-lane highway	MV: 120 km/h AV: 110 km/h	Light traffic	✗	Drowsiness	Age group, different time of the day, different sleepiness category	ANOVA	Karolinska Sleepiness Scale	• Time and driving mode have a significant effect on the development of drowsiness.
Bertholen and Gineyt (2014)	21–29	✗	At least 2 years of driving experience	Three-lane highway	Highway: 110 km/h Urban scenario: 70–90 km/h	With/ without	✗	Drunk driving	Driving environment (urban area, car following, highway), different alcohol concentration	ANOVA	Number of collisions, mean speed	• Lateral and longitudinal control of the AV is more likely to be impaired compared to strategies adopted in evasive situation.
Desmond et al. (1998)	18–27	✗	2 to 8 years of driving experience	Not considered	80 km/h	✗	✓	Fatigue	Perturbing events	ANOVA	• Physical fatigue items, perceptual fatigue items, boredom/apathy • Lateral control such as heading error, deviation of the vehicle	• A similar level of workload. • Better performance recovery in manual driving. • Automated driving results in undermobilizing driver's effort.

* This study used a series of driving simulator experiments with the same design.

References

Agriesti, S., Studer, L., Gandini, P., Marchionni, G., Ponti, M. & Visintainer, F. 2019. Safety on the Italian Highways: Impacts of the Highway Chauffeur System. *Smart Transportation Systems 2019.* Springer.

Arksey, H. & O'Malley, L. 2005. Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology,* 8**,** 19-32.

Arvin, R., Kamrani, M., Khattak, A. & Rios-Torres, J. Safety Impacts of Automated Vehicles in Mixed Traffic. Transportation Research Board Annual meeting, 2018 2018 Washington D.C., District of Columbia, United States of America.

Arvin, R., Khattak, A. & Rios Torres, J. Evaluating Safety with Automated Vehicles at Signalized Intersections: Application of Adaptive Cruise Control in Mixed Traffic. Transportation Research Board Annual meeting, 2019 2019 Washington D.C., District of Columbia, United States of America.

Awad, E., Dsouza, S., Kim, R., Schulz, J., Henrich, J., Shariff, A., Bonnefon, J.-F. & Rahwan, I. 2018. The moral machine experiment. *Nature,* 563**,** 59.

Bahram, M., Ghandeharioun, Z., Zahn, P., Baur, M., Huber, W. & Busch, F. Microscopic traffic simulation based evaluation of highly automated driving on highways. 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), 2014/11// 2014 Qingdao, China. IEEE, 1752-1757.

Banerjee, S. S., Jha, S., Cyriac, J., Kalbarczyk, Z. T. & Iyer, R. K. Hands off the wheel in autonomous vehicles?: A systems perspective on over a million miles of field data. 2018 48th Annual IEEE/IFIP International Conference on Dependable Systems and Networks (DSN), 2018. IEEE, 586-597.

Berthelon, C. & Gineyt, G. 2014. Effects of alcohol on automated and controlled driving performances. *Psychopharmacology,* 231**,** 2087-2095.

Bhavsar, P., Das, P., Paugh, M., Dey, K. & Chowdhury, M. 2017. Risk analysis of autonomous vehicles in mixed traffic streams. *Transportation Research Record,* 2625**,** 51-61.

Bila, C., Sivrikaya, F., Khan, M. A. & Albayrak, S. 2017. Vehicles of the future: A survey of research on safety issues. *IEEE Transactions on Intelligent Transportation Systems,* 18**,** 1046-1065.

Blommer, M., Curry, R., Kochhar, D., Swaminathan, R., Talamonti, W. & Tijerina, L. The effects of a scheduled driver engagement strategy in automated driving. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 2015. SAGE Publications Sage CA: Los Angeles, CA, 1681-1685.

Boggs, A. M., Wali, B. & Khattak, A. J. 2020. Exploratory analysis of automated vehicle crashes in California: a text analytics & hierarchical Bayesian heterogeneity-based approach. *Accident Analysis and Prevention,* 135**,** 105354.

Canis, B. 2020. Issues in Autonomous Vehicle Testing and Deployment. Congressional Research Service. Available: https://fas.org/sgp/crs/misc/R45985.pdf (April 2020).

Childress, S., Nichols, B., Charlton, B. & Coe, S. 2015. Using an activity-based model to explore the potential impacts of automated vehicles. *Journal of the Transportation Research Board,* 2493**,** 99-106.

Cohen, S. & Shirazi, S. 2017. Can We Advance Social Equity with Shared, Autonomous and Electric Vehicles? Institute of Transportation Studies at the University of California, Davis. Available: <https://www.transformca.org/sites/default/files/3R.Equity.Indesign.Final_.pdf> (January 2020).

Combs, T. S., Sandt, L. S., Clamann, M. P. & McDonald, N. C. 2019. Automated vehicles and pedestrian safety: exploring the promise and limits of pedestrian detection. *American journal of preventive medicine,* 56**,** 1-7.

Cui, J., Liew, L. S., Sabaliauskaite, G. & Zhou, F. 2019. A review on safety failures, security attacks, and available countermeasures for autonomous vehicles. *Ad Hoc Networks,* 90**,** 101823.

Deluka Tibljaš, A., Giuffrè, T., Surdonja, S. & Trubia, S. 2018. Introduction of Autonomous Vehicles: Roundabouts Design and Safety Performance Evaluation. *Sustainability,* 10**,** 1060-1060.

Desmond, P. A., Hancock, P. A. & Monette, J. L. 1998. Fatigue and automation-induced impairments in simulated driving performance. *Transportation Research Record,* 1628**,** 8-14.

Detwiller, M. & Gabler, H. C. Potential reduction in pedestrian collisions with an autonomous vehicle. The 25th ESV Conference Proceedings. NHTSA, 2017. 1-8.

Fagnant, D. J. & Kockelman, K. 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice,* 77**,** 167-181.

Favarò, F. M., Nader, N., Eurich, S. O., Tripp, M. & Varadaraju, N. 2017. Examining accident reports involving autonomous vehicles in California. *PLoS one,* 12**,** e0184952.

Gold, C., Happee, R. & Bengler, K. 2018. Modeling take-over performance in level 3 conditionally automated vehicles. *Accident Analysis & Prevention,* 116**,** 3-13.

Goodall, N. J. 2014. Ethical decision making during automated vehicle crashes. *Transportation Research Record,* 2424**,** 58-65.

Gouy, M., Diels, C., Reed[1], N., Stevens[1], A. & Burnett, G. 2012. The effects of short time headways within automated vehicle platoons on other drivers.

Happee, R., Gold, C., Radlmayr, J., Hergeth, S. & Bengler, K. 2017. Take-over performance in evasive manoeuvres. *Accident Analysis & Prevention,* 106**,** 211-222.

Hendrickson, C. T. & Harper, C. 2018. Safety and Cost Assessment of Connected and Automated Vehicles.

Jafarnejad, S., Codeca, L., Bronzi, W., Frank, R. & Engel, T. A car hacking experiment: When connectivity meets vulnerability. 2015 IEEE Globecom Workshops (GC Wkshps), 2015. IEEE, 1-6.

Junietz, P., Wachenfeld, W., Klonecki, K. & Winner, H. Evaluation of Different Approaches to Address Safety Validation of Automated Driving. 2018 21st International Conference on Intelligent Transportation Systems (ITSC), 2018. IEEE, 491-496.

Kalra, N. 2017. *Challenges and approaches to realizing autonomous vehicle safety,* Santa Monica, CA, RAND Corporation.

Kalra, N. & Paddock, S. M. 2016. Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability? *Transportation Research Part A: Policy and Practice,* 94**,** 182-193.

Katrakazas, C., Quddus, M. & Chen, W. H. 2019. A new integrated collision risk assessment methodology for autonomous vehicles. *Accident Analysis and Prevention,* 127**,** 61-79.

Kockelman, K., Avery, P., Bansal, P., Boyles, S. D., Bujanovic, P., Choudhary, T., Clements, L., Domnenko, G., Fagnant, D. & Helsel, J. 2016. Implications of connected and automated vehicles on the safety and operations of roadway networks: A final report. Center for Transportation Research, University of Texas at Austin. FHWA/TX-16/0-6849-1, Available: <https://library.ctr.utexas.edu/ctr-publications/0-6849-1.pdf> (January 2019).

Koopman, P. & Wagner, M. 2016. Challenges in autonomous vehicle testing and validation. *SAE International Journal of Transportation Safety,* 4**,** 15-24.

Kundinger, T., Riener, A., Sofra, N. & Weigl, K. Drowsiness Detection and Warning in Manual and Automated Driving: Results from Subjective Evaluation. Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 2018. 229-236.

Kusano, K. D. & Gabler, H. C. 2014. Comprehensive target populations for current active safety systems using national crash databases. *Traffic injury prevention,* 15**,** 753-761.

Lee, C. 2017. Grabbing the wheel early: Moving forward on cybersecurity and privacy protections for driverless cars. *Federal Communations Law Journal,* 69**,** 25.

Lee, S., Oh, C. & Hong, S. 2018. Exploring lane change safety issues for manually driven vehicles in vehicle platooning environments. *IET Intelligent Transport Systems,* 12**,** 1142-1147.

Li, R. & Zhai, R. Estimation and Analysis of Minimum Traveling Distance in Self-driving Vehicle to Prove Their Safety on Road Test. Journal of Physics: Conference Series, 2019. IOP Publishing, 032101.

Li, T. & Kockelman, K. M. Valuing the safety benefits of connected and automated vehicle technologies. Transportation Research Board 95th Annual Meeting, 2016.

Litman, T. 2017. Autonomous vehicle implementation predictions. Victoria Transport Policy Institute Victoria, Canada. Available: <https://www.vtpi.org/avip.pdf> (January 2019).

Lubbe, L., Jeppsson, H., Ranjbar, A., Fredriksson, J., Bärgman, J. & Östling, M. Predicted road traffic fatalities in Germany: The potential and limitations of vehicle safety technologies from passive safety to highly automated driving. Proceedings of IRCOBI conference. Athena, Greece, 2018.

Matysiak, A. & Razin, P. Analysis of the advancements in real-life performance of highly automated vehicles' with regard to the road traffic safety. MATEC Web of Conferences, 2018. EDP Sciences, 05003.

Milakis, D., Van Arem, B. & Van Wee, B. 2017. Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems,* 21**,** 324-348.

Morando, M. M., Tian, Q., Truong, L. T. & Vu, H. L. 2018. Studying the Safety Impact of Autonomous Vehicles Using Simulation-Based Surrogate Safety Measures. *Journal of Advanced Transportation*.

Munn, Z., Peters, M. D., Stern, C., Tufanaru, C., McArthur, A. & Aromataris, E. 2018. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Medical Research Methodology,* 18**,** 143.

NHTSA 2018. Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey. U.S. Department of Transportation. Available: <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812506> (March 2020).

Papadoulis, A., Quddus, M. & Imprialou, M. 2019. Evaluating the safety impact of connected and autonomous vehicles on motorways. *Accident Analysis and Prevention,* 124**,** 12-22.

Petrović, Đ., Mijailović, R. & Pešić, D. 2020. Traffic Accidents with Autonomous Vehicles: Type of Collisions, Manoeuvres and Errors of Conventional Vehicles' Drivers. *Transportation Research Procedia,* 45**,** 161-168.

PTV 2018. *PTV VISSIM Manual*.

Qin, Y. & Wang, H. 2019. Influence of the feedback links of connected and automated vehicle on rear-end collision risks with vehicle-to-vehicle communication. *Traffic Injury Prevention,* 20**,** 79-83.

Rahman, M. S., Abdel-Aty, M., Lee, J. & Rahman, M. H. 2019. Safety benefits of arterials' crash risk under connected and automated vehicles. *Transportation Research Part C: Emerging Technologies,* 100**,** 354-371.

Raj, A., Kumar, J. A. & Bansal, P. 2019. A Multicriteria Decision Making Approach to Study the Barriers to the Adoption of Autonomous Vehicles. *arXiv preprint arXiv:.12051*.

Rau, P., Yanagisawa, M. & Najm, W. G. Target crash population of automated vehicles. In 24th International Technical Conference on the Enhanced Safety of Vehicles (ESV), 2015. 1-11.

Rodrigue, J.-P., Comtois, C. & Slack, B. 2016. *The geography of transport systems*, Routledge.

SAE 2018. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. Available: <https://www.sae.org/standards/content/j3016_201806/> (November 2019).

Schoettle, B. & Sivak, M. 2015. A preliminary analysis of real-world crashes involving self-driving vehicles. The University of Michigan, Transportation Research Institute. UMTRI-2015-34,

Sener, I. N., Zmud, J. & Williams, T. 2019. Measures of baseline intent to use automated vehicles: a case study of Texas cities. *Transportation Research Part F: Traffic Psychology and Behaviour,* 62**,** 66-77.

Sohrabi, S. & Khreis, H. 2020. Burden of disease from transportation noise and motor vehicle crashes: Analysis of data from Houston, Texas. *Environment International***,** 105520.

Sohrabi, S., Khreis, H. & Lord, D. 2020. Impacts of Autonomous Vehicles on Public Health: A Conceptual Model and Policy Recommendations. *Sustainable Cities and Society,* 63**,** 102457.

Strand, N., Nilsson, J., Karlsson, I. M. & Nilsson, L. 2014. Semi-automated versus highly automated driving in critical situations caused by automation failures. *Transportation research part F: traffic psychology and behaviour,* 27**,** 218-228.

Taeihagh, A. & Lim, H. S. M. 2018. Governing autonomous vehicles: emerging responses for safety, liability, privacy, cybersecurity, and industry risks. *Transport Reviews,* 39**,** 103-128.

Tainio, M. 2015. Burden of disease caused by local transport in Warsaw, Poland. *Journal of Transport and Health,* 2**,** 423-433.

Teoh, E. R. & Kidd, D. G. 2017. Rage against the machine? Google's self-driving cars versus human drivers. *Journal of Safety Research,* 63**,** 57-60.

US DOT 2018. Preparing for the Future of Transportation: Automated Vehicles 3.0.

Virdi, N., Grzybowska, H., Waller, S. T. & Dixit, V. 2019. A safety assessment of mixed fleets with Connected and Autonomous Vehicles using the Surrogate Safety Assessment Module. *Accident Analysis and Prevention,* 131**,** 95-111.

Wang, L., Zhong, H., Ma, W., Abdel-Aty, M. & Park, J. 2020. How many crashes can connected vehicle and automated vehicle technologies prevent: A meta-analysis. *Accident Analysis and Prevention,* 136**,** 105299.

Wang, S. & Li, Z. 2019. Exploring the mechanism of crashes with automated vehicles using statistical modeling approaches. *PloS One,* 14.

Wilde, G. J. 1998. Risk homeostasis theory: an overview. *Injury Prevention,* 4**,** 89-91.

Xu, C., Ding, Z., Wang, C. & Li, Z. 2019. Statistical analysis of the patterns and characteristics of connected and autonomous vehicle involved crashes. *Journal of Safety Research,* 71**,** 41-47.

Yanagisawa, M., Najm, W. G. & Rau, P. Preliminary Estimates Of Target Crash Populations For Concept Automated Vehicle Functions. 25th International Technical Conference on the Enhanced Safety of Vehicles (ESV), 2017.

Yang, J., Ward, M. & Akhtar, J. 2017. The development of safety cases for an autonomous vehicle: A comparative study on different methods. SAE Technical Paper. 0148-7191*,* Available: <https://saemobilus.sae.org/content/2017-01-2010> (January 2019).

Ye, L. & Yamamoto, T. 2019. Evaluating the impact of connected and autonomous vehicles on traffic safety. *Physica A: Statistical Mechanics and its Applications,* 526**,** 121009-121009.

Young, W., Sobhani, A., Lenné, M. G. & Sarvi, M. 2014. Simulation of safety: A review of the state of the art in road safety simulation modelling. *Accident Analysis and Prevention,* 66**,** 89-103.

Zhang, W., Guhathakurta, S., Fang, J. & Zhang, G. 2015. Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society,* 19**,** 34-45.