Chapter 5 - Safety of Mixed Traffic: Evidence from Empirical Studies

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Abstract

Given the potential limitation of the simulation-based approach (e.g., various model assumptions, unreal conditions), this chapter mainly focuses on reviewing existing empirical studies on traffic safety in mixed traffic, which includes reactive safety analysis of mixed traffic (i.e., the analysis of mixed traffic crashes) and proactive safety analysis of mixed traffic. In this chapter, we will summarize and discuss the main findings across existing empirical studies and highlight future research directions.

5.1 Simulation-based Mixed Traffic Safety Research

The simulation-based approach has been intensively used for mixed traffic research in the past few years and has shown a great advantage in exploring the effects of connected and automated vehicles (CAVs) on mixed traffic safety, especially under different penetration rates of CAVs. For example, by using different car-following models to capture characteristics of different types of vehicles (e.g., human-driven vehicles (HDVs) and cooperative adaptive cruise control (CACC) vehicles), Yao et al. (2020) investigated the safety of mixed traffic flow on expressways under different penetration rates of CAVs using multiple safety measures (i.e., standard deviation of vehicle speed, time-exposed rear-end crash risk, time-exposed time-to-collision and time-integrated time-to-collision), and they found that the increase of CACC vehicles reduces traffic safety risks significantly when the penetration rate exceeds 50%. Similarly, Ye & Yamamoto (2019) analyzed the impact of CAVs on traffic safety under various penetration rates, in which the frequency of dangerous situations and time-to-collision were used as indicators of traffic safety. They revealed that the condition of traffic safety is greatly improved with the increase in CAV penetration rate, while a more cautious car-following strategy of the CAV would contribute more to traffic safety. Jiang et al. (2023) explored the impact of platoon size on the safety of mixed traffic flows through numerical simulations, and they found that the effect of platoon size of CAVs on the safety of mixed traffic flow was influenced by the CAV penetration rate. Specifically, when the platoon size reaches 2 to 3, the mixed traffic flow is safer when the penetration rate of CAVs is lower than 40%. By using the CACC car following models, Arvin et al. (2021) also found that the safety of mixed traffic flow improved substantially with a penetration rate of more than 40%. Garg & Bouroche (2023) investigated the detrimental effects of unreliable vehicle-to-vehicle (V2V) communication and large reaction times on the safety of mixed traffic flow evaluated by the number of safety conflicts, and they found that, at 70% penetration rates, CAVs could reduce 66.67% of the safety conflicts in the presence of unreliable V2V communication (i.e., packet drop of 70%) and large reaction times (i.e., 0.5 s) by adopting a very cautious car-following strategy.

However, there are several major limitations of simulation-based studies. First, the behaviors of HDVs and CAVs in the simulation were typically modeled using various car-following models (e.g., Intelligent Driver Model, Gipps Model, Wiedemann Model, CACC model), while these models posed different assumptions and may not fully reflect the behaviors of vehicles under real conditions. Second, human drivers may have different attitudes toward CAVs and may interact with CAVs differently, and there might even be potential adaptation among human drivers, which is difficult for simulation-based studies to account for. Next, most simulation-based studies assumed that CAVs operated in traffic scenarios with perfect communication or with only a very small number of vehicles having imperfect communication, which may not be the case in real conditions. Finally, existing studies using simulation-based methods intensively considered the effects of penetration rates on the safety of mixed traffic flow, while it may take a long time to reach the penetration rates settled in those studies.

Therefore, to provide more realistic insights about the current mixed traffic safety, in this Chapter, we will mainly review the research that adopted empirical methods, i.e., a method that gains knowledge or obtains empirical evidence through direct and indirect observation or experience. Specifically, we will discuss mixed traffic safety from two perspectives: mixed traffic safety analysis (i.e., crash analysis and surrogate measures analysis in mixed traffic) and mixed traffic behavioral analysis. We will discuss the major findings from existing research that focused on safety in mixed traffic.

5.2 Reactive Safety Analysis of Mixed Traffic

As many companies (e.g., Waymo in the US and Baidu in China) have been testing their automated vehicles (AV) on publicly open roads, many AV-involved crashes (or mixed traffic crashes) have already happened in the past few years. There were several public AV-involved crash report datasets available and interested readers could refer to Table 2.2.3 in this book for more information. We first discussed the approaches that existing studies used to analyze AV-involved crashes and highlighted some useful considerations for crash analysis. Furthermore, we summarized the characteristics of mixed traffic crashes from the following four perspectives: prevalence of mixed traffic crashes, dominant role of rear-end crashes, factors associated with mixed traffic crashes, and factors affecting mixed traffic crash outcomes.

A. Approaches for Crash Analysis

Previous studies have adopted various approaches to analyze AV crashes. In the early stages of AV testing (e.g., 2014-2018), AV crashes were mainly analyzed through descriptive statistics (Dixit et al., 2016; Favarò et al., 2017), potentially due to the limited sample size at that time. With the increasing number of crash records, some studies tried to identify the contributing factors of crash severity and collision type in AV crashes through statistical modeling or machine learning methods, such as logistic regression (Boggs et al., 2020; Wang and Li, 2019; Xu et al., 2019), classification and regression tree (CART) (Chen et al., 2020; Wang and Li, 2019), cluster analysis (Song et al., 2021), decision tree (Ashraf et al., 2021), association rule method (Ashraf et al., 2021; Liu et al., 2024), and extreme gradient boosting (XGBoost) (Chen et al., 2020). There were also some studies trying to investigate the characteristics of AV crashes by performing text-analytic-based methods on the narratives of

AV crash reports (Alambeigi et al., 2020; Boggs et al., 2020; Kutela et al., 2022b; Lee et al., 2023). Some studies also adopted Bayesian-related methods to serve different purposes. For example, the hierarchical Bayes logit models were used for accounting for unobserved heterogeneity (Boggs et al., 2020), Bayesian latent class models were used to identify crash patterns (Das et al., 2020), and Bayesian networks (BN) to reveal interrelationships among influential factors of AV crashes (Kutela et al., 2022a; Lee et al., 2023). Table 5.2.1 summarizes the approaches used by previous studies to analyze mixed traffic crashes.

Table 5.2.1 Summary of Approaches Used by Previous Studies to Analyze Mixed Traffic Crashes

Type of approaches	Approaches and corresponding studies
1. Descriptive statistics	Descriptive statistics (Dixit et al., 2016; Favarò et al., 2017)
2. Statistical modelling	Logistic regression (Boggs et al., 2020; Huang et al., 2023b; Wang and Li, 2019; Xu et al., 2019)
3. Machine learning methods	Classification and regression tree (CART) (Chen et al., 2020; Wang and Li, 2019); Cluster analysis (Song et al., 2021); Decision tree (Ashraf et al., 2021); Association rule method (Ashraf et al., 2021; Liu et al., 2024); Extreme gradient boosting (XGBoost) (Chen et al., 2020)
4. Text-analytic-based methods	Topic modelling and text mining (Alambeigi et al., 2020; Boggs et al., 2020; Kutela et al., 2022b; Lee et al., 2023)
5. Bayesian-related methods	Hierarchical Bayes logit models (Boggs et al., 2020); Bayesian latent class models (Das et al., 2020); Bayesian networks (Kutela et al., 2022a; Lee et al., 2023)

B. Characteristics of Mixed Traffic Crashes

(1) The Prevalence of Mixed Traffic Crashes

As the most representative and intuitive indicator of mixed traffic safety, the prevalence of crashes was widely evaluated using the crash rate data. Schoettle & Sivak (2015) conducted the first preliminary analysis to investigate the crash rates of AVs operated by three companies (i.e., Google, Delphi, and Audi) in California, and they further compared it to the crash rate of conventional vehicles in the US in 2013. They found that AVs have a higher crash rate (i.e., 9.1 crashes per million miles) than conventional vehicles (i.e., 4.1 crashes per million miles), though not statistically significant. It should be noted that, at the time, only 11 AV-involved crashes over 1.2 million miles were reported. In other words, the accumulated mileage of AVs was limited, and their exposure may not be comparable to the exposure of conventional vehicles.

Later, in 2016, Blanco et al. (2016) conducted another more comprehensive comparison between crash rates of AVs and conventional vehicles. They used internal data (including written reports, video, and vehicle kinematic data) from Google's Self-Driving Car program

(about 1.3 million miles) and the data from the Second Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS) (Blanco et al., 2016). Initially, they found that the AV crash rate (i.e., 8.7 crashes per million miles) was higher than that of conventional vehicles (i.e., 1.9 crashes per million miles) when the crash severity and reporting requirements were not controlled. However, when unreported crashes were controlled, the AV crash rates (i.e., 3.2 crashes per million miles) were lower than that of conventional vehicles (i.e., 4.2 crashes per million miles). According to the classifications of crash severity in SHRP 2 NDS, they also compared the crash severity-controlled AV crash rates to the SHRP 2 age-adjusted crash rates. Results indicated that AVs had lower rates of severe crashes (i.e., 1.6 crashes per million miles for both Level 1 and Level 2 crashes) when compared to conventional vehicles (i.e., 2.5 crashes per million miles for Level 1 crashes and 3.3 crashes per million miles for Level 2 crashes). However, the rates of less severe AV crashes (i.e., Level 3 crashes, 5.6 crashes per million miles) were significantly lower than the rates of conventional vehicles (i.e., 14.4 crashes per million miles).

Based on the crash reports collected by the California Department of Motor Vehicles (CA-DMV) between September 2014 and November 2015 (in total of 12 crashes), Dixit et al. (2016) estimated that the Google AV crash rate was 1 crash for every 47,148 miles, which was much higher than the crash rate of conventional vehicles (i.e., 1 crash for every 2.07 million miles) estimated from the California Highway Patrol (CHP) Safety Database from 2014 (Dixit et al., 2016). Two potential issues may influence the results: (1) The crash severity was not adjusted, as CA-DMV AV crash reports include all crashes while CHP crash reports only include crashes that met the reporting criteria; (2) The AVs were tested in the local streets at that time while the CHP database only covered State, US, and Interstate roads.

Favarò et al. (2017) also estimated the AV crash rates using the crash reports collected by CA-DMV between September 2014 and March 2017 (in total 26 crashes), and they found that the AV crash rates were 42,017 miles per crash (Favarò et al., 2017). To conduct the comparison, they estimated the crash rates of conventional vehicles based on the data from the National Highway Traffic Safety Administration (NHTSA) and Federal Highway Administration (FHWA), and they found that the crash rates of conventional vehicles (i.e., 500,000 miles per crash) were lower than that of AVs. Similarly, Banerjee et al. (2018) compared the AV crash rates between 2014 and 2017 with the crash rates of conventional vehicles from NHTSA and FHWA (Banerjee et al., 2018), they found that the Google AV crash rates (i.e., 41.4 crashes per million miles) were 20 times higher than the crash rates of conventional vehicles (i.e., 2 crashes per million miles). However, both Favarò et al. (2017) and Banerjee et al. (2018) compared all AV-involved crashes with police-reported crashes of conventional vehicles while not adjusting for the underreporting issue of conventional vehicle crashes.

To account for the under-reporting issue of conventional vehicle crashes, Teoh and Kidd (2017) coded Google AV crashes by type and severity through narratives released by Google, and they calculated the crash rates using crashes that were severe enough to be reportable to police (Teoh and Kidd, 2017). These police-reportable AV crash rates were compared with policed-reported crash rates for conventional vehicles between 2009 and 2015 in several regions, which included Mountain View, Santa Clara County, California, and the US. They found that AV crash rates (i.e., 2.19 crashes per million miles) were lower than the crash rates of conventional vehicles

in the US (i.e., 3.59 crashes per million miles) and Mountain View (i.e., 6.06 crashes per million miles), while higher than the crash rates of conventional vehicles in Santa Clara County (i.e., 1.35 crashes per million miles) and California (i.e., 1.92 crashes per million miles). The authors also compared the Google AV crash rates with the crash rates of conventional vehicles in SHRP 2 NDS, and results indicated that the Google AV crash rates (i.e., 9.65 crashes per million miles) were significantly lower than the crash rates of conventional vehicles in SHRP 2 NDS (i.e., 27.60 crashes per million miles). However, it should be noted that the crash rates of conventional vehicles in SHRP 2 NDS in this study are not age-adjusted, thus might be overcounting as the SHRP 2 NDS oversampled teen and elderly drivers who were known to have higher crash risks (Regev et al., 2018).

Given the high prevalence of rear-end collisions among AV-involved crashes, Goodall (2021) specifically compared the AV struck-from-behind crash rates with the national crash rates of conventional vehicles using the same crash definitions. The AV crash rates were filtered and extracted from the CA-DMV dataset, while the crash rates of conventional vehicles were calculated based on the SHRP 2 NDS, after weighing the age by the US driving population. The AVs were found to be struck from behind at 4.8 times the rate of conventional vehicles, while the AV crash rates were 5 times higher for urban driving when controlling for the driving environment. One potential reason for this could be that AVs were tested more in urban areas. In another study, Goodall (2024) shifted the focus from AVs to partial AVs (i.e., vehicles equipped with advanced driver assistance systems) (Goodall, 2024), in which they compared the crash rates of vehicles equipped with Society of Automobile Engineers (SAE) Level 1 automation and SAE Level 2 automation, with road type and age controlled. It was found that Level 2 vehicles only decreased the crash rates by 10% when controlling for different rates of freeway driving, even though the Level 2 vehicles were claimed to have a 43% lower crash rate than Level 1 vehicles (Goodall, 2024).

Table 5.2.2 summarizes the comparison of crash rates of AVs and conventional vehicles in existing studies. It can be observed that the results were somewhat mixed as different studies used different data sources for calculating the crash rates of AVs and conventional vehicles, and some studies adopted the adjustment to account for underreporting (e.g., Teoh & Kidd, 2017) and imbalanced age distribution (e.g., Goodall, 2021) while some studies did not. Therefore, it is difficult to judge the safety performance of AVs based on the current studies, as technologies continue to mature. Inspired by existing studies, we highly encourage future studies to account for potential bias while estimating crash rates (i.e., considering the exposure and underreporting crashes) and make fair comparisons.

Table 5.2.2 Comparison of Crash Rates of AVs and Conventional Vehicles

AV Crashes Source	Crash Rates of AVs in per Million Miles [95% Confidence Interval]	Conventional Vehicle Crashes Source	Crash Rates of Conventional Vehicles in per Million Miles [95% Confidence Interval]	Source
All crashes	9.1 [4.5, 16.3]	Police-reportable crashes	4.1 [4.5, 16.3]	Schoettle & Sivak (2015)
Severity-adjusted	3.2 [0.4, 11.4]	NHTSA Police-reportable crashes	4.2 [2.8, 9.9]	Blanco et al.

Waymo crashes				(2016)
Severity-adjusted Waymo crashes	3.2 [0.4, 11.4]	Age-adjusted SHRP 2 Police-reportable crashes	5.8 [4.7, 7.0]	Blanco et al. (2016)
All crashes	21.21	CHP reported crashes with a limited range	0.48	Dixit et al. (2016)
All crashes	23.80	NHTSA and FWHA reported crashes	2.0	Favarò et al. (2017)
All crashes	41.4	NHTSA and FWHA reported crashes	2.0	Banerjee et al. (2018)
All crashes	9.65 [5.81, 15.07]	All SHRP 2 crashes (not adjusted)	27.60 [25.77, 29.53]	Teoh & Kidd (2017)
Police-reportable crashes	2.19 [0.44, 6.39]	Police-reportable crashes in US	3.59 [2.31, 4.87]	Teoh & Kidd (2017)
All Google rear-end struck	7.11 [3.89, 11.93]	SHRP 2 rear-end struck	2.65 [2.10, 3.29]	Teoh & Kidd (2017)
All AV struck-from-behind crashes	17.2 [14.2, 20.7]	Age-adjusted SHRP 2 struck-from-behind crashes	3.6 [3.0, 4.3]	N. J. Goodall (2021)

At the same time, as a macroscopic indicator, the crash rate alone can provide the overall map of mixed traffic safety, while it may not reveal factors leading to crashes from a microscopic perspective. To guide the design and optimization of countermeasures that can improve the safety of mixed traffic, researchers tried to investigate other characteristics of mixed traffic crashes. We summarized the detailed characteristics of mixed traffic crashes in the following three perspectives: the dominant role of rear-end crashes, factors associated with AV crashes, and factors associated with AV crash outcomes.

(2) The Dominant Role of Rear-end Crashes

Rear-end crashes dominated the AV-involved mixed traffic crashes. One of the most representative characteristics of the mixed traffic crashes was that rear-end crashes dominated the AV-involved mixed traffic crashes. For example, Lee et al. (2023) found that 51.9% of 260 AV crashes from 2019 to 2021 were rear-end crashes, and when there was a crash, AVs were more vulnerable to rear-end collisions in the automated driving mode than in the conventional mode (Lee et al., 2023); Kutela, Avelar, et al. (2022) found that 63.5% of 333 AV crashes from 2017 to 2021 were rear-end crashes, while AVs were at fault for only 14.4% of the crashes (Kutela et al., 2022a). Xu et al. (2019) found that two predominant collision types among AV crashes were rear-end and sideswipe crashes, which accounted for 57.5% and 28.8% of AV crashes, respectively (Xu et al., 2019). By comparing AV crashes with conventional vehicle crashes, Liu et al. (2021) found that the most frequent AV pre-crash scenarios were rear-ended

collisions (52.46%) and lane change collisions (18.85%), with the proportion of AVs rear-ended by conventional vehicles occurring with a frequency 1.6 times that of conventional vehicles (Liu et al., 2021). Similar findings were also obtained in Favarò (2017) (Favarò et al., 2017).

Situations when AVs being rear-ended by HVs. Given the high prevalence of rear-end crashes, some studies tried to understand the characteristics of these rear-end crashes. For instance, based on the AV crash reports from 2015 to 2020 collected by CA-DMV, McCarthy (2022) found that most AV crashes are the fault of human drivers, with AVs being rear-ended by HVs, which implies that human drivers appear less able to anticipate the AV's more conservative driving style. More specifically, several studies also revealed that most rear-end crashes occurred when AVs were stopped at intersections, while HVs were proceeding straight through the intersection (Ashraf et al., 2021; Liu et al., 2024). Based on a crash sequence analysis of 168 AV crashes reported to CA-DMV from 2015 to 2019, Song et al., (2021) found that the most representative pattern in AV crashes was "collision following AV stop". Through analyzing the AV crash reports collected by NHTSA between July 2021 and May 2022, Huang et al. (2023) also found that the likelihood of an AV-involved crash being a rear-end collision would be the highest when the following HV was proceeding straight. With 251 AV crash reports from CA-DMV as of February 2020, Ashraf et al. (2021) extracted the pre-crash motion of AV crashes using the decision tree and association rule methods, by which they found that the most frequent types of AV crashes were rear-end crashes and predominantly occurred at intersections when AVs were stopped and engaged in the automated driving mode. Compared to conventional vehicles, AVs were less likely to be involved in a collision from the front of the vehicle, such as hitting an object ahead (Novat et al., 2023). This important feature of AVs being struck from behind in AV-involved crashes was also evidenced by the safety performance data of Waymo (Schwall et al., 2020).

Various factors were found to be associated with AV-involved rear-end crashes. Several studies further explored the factors that were associated with rear-end crashes. The most common phenomenon was AV rear-ended by HVs. For example, Lee et al (2023) investigated the interrelationships among pre-crash conditions, and they found that AVs were more likely to be rear-ended in the automated driving mode compared to the conventional mode, which means that AVs might not be capable enough to avoid rear-end collisions compared to HVs. At the same time, Lee et al. (2023) also revealed that there was no significant difference in the chance of rear-end collisions when comparing the conventional mode and manual disengagement, which means that an AV will be less likely to have a rear-end collision when it hands over the control to a human driver in case of emergency. Similarly, through analysis of event transition in the crash sequences, Song et al (2021) found that the disengagement had a transition probability of 68% to an immediate collision, which has also been observed in Boggs et al (2020), which found that when the automated driving system was engaged and remained engaged, the likelihood of an AV-involved rear-end crash was substantially higher compared to a conventionally driven AV or when the driver disengages the automated driving system before a crash. Xu et al. (2019) also found that AV crashes that occurred under the automated driving mode were more likely to be rear-end crashes, and the crashes were more likely to be rear-end crashes when AVs were stopped or when AVs had turning movements (Xu et al., 2019). Besides, by comparing AV crashes with conventional vehicle crashes, Novat et al.,

(2023) revealed that AVs were more likely to be involved in rear-end collisions in signalized intersections and lanes with less than 45 miles per hour (mph) speed limit. Petrović et al (2020) also indicated that drivers' typical errors of conventional vehicles in AV crashes were "unsafe speed" and "following too closely". Kutela, Avelar, et al. (2022) also found that the chances of rear-end crashes were lower in the parking lot, and when nonvehicular participants were involved, but increased in high-traffic flow roadways (Kutela et al., 2022a).

Based on the findings from existing studies, it is straightforward to see the dominant role of rear-end crashes in AV crashes, and in most cases, the AVs were rear-ended by HVs at intersections when AVs stopped or drove slowly. Given the factors associated with AV-involved rear-end crashes, the reasons behind this phenomenon were two-fold: (1) From the perspective of AV, current AVs had limited perception and prediction capability, thus adopted comparably conservative driving styles, and usually would stop or drive slowly at the intersection faced with the complex environment and interaction with various road agents (e.g., pedestrians, HVs, traffic lights); (2) From the perspective of HV, human drivers may not develop an appropriate mental model of current AVs (Huang et al., 2023), thus might drive in a more aggressive way (e.g., following too close with high speed) and could not anticipate AVs' behaviors.

(3) Factors Associated with AV Crashes

To provide more insights into the design of relevant countermeasures, some studies also investigated the factors associated with AV crashes, and they found that various environment-related and motion-related factors were associated with AV crashes.

In terms of environmental-related factors, Kutela et al (2022) found that crosswalks, intersections, and traffic signals are the key predictors of VRUs-AV-related crashes, in which bicyclists and scooterists were more likely to be involved in the AV crashes directly, while pedestrians were more likely to be involved in the AV crashes indirectly. In another study, Kutela, Avelar, et al. (2022) shifted the research focus to vehicle at-fault and collision type of AV crashes (Kutela et al., 2022a), and they found that the chance of an AV being at fault seems higher in parking locations, and during driving on wet pavements in unclear weather conditions. Liu et al. (2024) also found that AV crashes are more likely to occur in poor lighting conditions (e.g., night), unsignalized intersections, and two-way roads without a median (Liu et al., 2024).

In terms of motion-related factors, Alambeigi et al. (2020) found that the AV crash narratives include five topics: (1) transitions of control; (2) collisions at intersections in a right-turn lane; (3) collisions at intersections in non-turn lanes; (4) side-swipe crashes during a left-overtake; and (5) collisions at intersections involving oncoming traffic (Alambeigi et al., 2020). Kutela, Das, et al. (2022) also found that the movements of AVs (i.e., turning, slowing down, stopping) are the key predictors of VRUs-AV-related crashes (Kutela et al., 2022b). Besides, Liu et al. (2021) summarized three important causes for AV crashes (Liu et al., 2021): (1) The perception-reaction time difference between AVs and human drivers; (2) AV's inaccurate identification of the intention of other vehicles to change lanes; and (3) AV's insufficient path planning in both spatial and temporal dimensions.

Interestingly, Ashraf et al. (2021) found that all types of AV crashes occurred mainly due to HVs (Ashraf et al., 2021). For example, rear-end crashes occurred because HVs failed to react appropriately to leading stopped AVs at intersections, while broadside, sideswipe, and head-on crashes occurred because of HVs' unsafe movements, red-light running, or disobeying the stop sign at the intersection.

To summarize, previous studies have identified various factors associated with AV crashes, and these factors could be categorized into two categories: (1) Environment-related factors, which include roadway types (e.g., crosswalks, intersections, parking lots, two-way roads without a median), traffic signals, weather, and lighting; (2) Motion-related factors, which include various movements of AVs (e.g., turning, slowing down, and stopping).

(4) Factors Influencing AV Crash Outcomes

The injury severity level of road agents is a commonly adopted metric of crash outcomes (e.g., Abdel-Aty & Keller, 2005; Kockelman & Kweon, 2002; Savolainen et al., 2011). Thus, previous research also analyzed factors associated with the injury severity level in AV-involved crashes, from which we categorized the factors associated with AV crash severity into three categories: collision factor, AV factor, and environmental factor.

In terms of collision factor, rear-end collision was found to be associated with higher crash severity. For example, by using the property-damage-only (PDO) crash as the reference level, Xu et al. (2019) found that the severity level of rear-end crashes was higher than that of other types of collisions. Similarly, based on the Bayesian latent class model, Das et al. (2020) identified six classes of AV crash patterns, in which the class associated with rear-end collisions was also associated with a higher proportion of injury severity level (i.e., the percentage of the operator severity is more than 5 times higher than no severity condition). In addition, Das et al. (2020) also found that multi-vehicle collisions were associated with a higher proportion of injury severity level (i.e., the percentage of the operator severity is more than 2 times higher than no severity condition).

For the AV factor, both Xu et al. (2019) and Boggs et al. (2020) found that an increase in crash severity was positively associated with roadside parking. Das et al. (2020) also found that the AV crash pattern class associated with turning was associated with a higher proportion of injury severity level. Besides, irrespective of the collision type, when the AV was at fault, the chance of physical injury in a crash increased significantly (Kutela et al., 2022a; Wang and Li, 2019).

In terms of environment-related factors, Xu et al. (2019) found that AV crashes that occurred on one-way roads were more likely to be PDO crashes compared with AV crashes that occurred on other more complex roads. Chen et al. (2020) revealed that crash severity significantly increased when the AVs collided at an intersection under extreme weather conditions (e.g., fog and snow). Compared to areas where land-use patterns were less diverse, an AV crash resulting in injuries also had a higher likelihood of occurring in areas where land-use patterns were more diverse. Kutela, Avelar, et al. (2022) also found that the likelihood of physical injury is higher at high-speed, intersections, and wet pavements. Similarly, Yan, Huang, & He et al. (2023) found that a wet road surface significantly increased the probability of injury in AV crashes.

Wang & Li (2019) also identified the highway as the location where severe injuries were likely to happen. Based on the Bayesian latent class model, Das et al. (2020) identified six classes of AV crash patterns, in which classes associated with dark lighting conditions with streetlights, were also associated with a higher proportion of injury severity level compared to other AV crash pattern classes. Boggs et al. (2020) found that injury crashes were positively associated with roadside parking, intersections, and arterial roads, while Lee et al. (2023) found that injury crashes were more likely to occur on a ramp or slip lane. Interestingly, P. Liu et al. (2024) found that the mechanisms for AV crashes with different severities were different. For example, no damage and minor injured crashes were more likely to be associated with the road features (e.g., road surface conditions) and traffic conditions (e.g., intersection controls), while severe damage crashes are more likely to occur in a chain of events involving poor visibility, slippery road surface, and fixed objects.

Table 5.2.3 summarizes the factors that were associated with high injury severity levels in AV-involved crashes. In all, existing studies have revealed several types of risky factors that were associated with high crash severity, which include collision factor (e.g., rear-end collision), AV factor (e.g., AV at fault), and environmental factor (e.g., road, weather, lighting). These factors could be considered valuable references when designing relevant countermeasures for enhancing mixed traffic safety.

Table 5.2.3 Factors Associated with High Injury Severity Levels in AV-involved Crashes

Factor category	Factors associated with high injury severity levels	Source
Collision factor	Multi-vehicle collisions	Das et al., (2020)
	Rear-end collisions	Boggs et al., (2020); Das et al., (2020); Xu et al., (2019)
AV factor	Turning	Das et al., (2020)
	Roadside parking	Boggs et al., (2020); Xu et al., (2019)
	AV at fault	Kutela, Avelar, et al., (2022); S. Wang & Li, (2019)
Environment-related factor	Wet pavements	Kutela, Avelar, et al., (2022); P. Liu et al., (2024); Yan, Huang, & He, (2023)
	High-speed locations	Kutela, Avelar, et al., (2022); S. Wang & Li, (2019)
	Intersections	Boggs et al., (2020); Chen et al., (2020)
	Extreme weather conditions (e.g., fog and snow)	Chen et al., (2020)
	Complex roads, Diverse lane-use patterns	Chen et al., (2020; Xu et al., (2019)
	Dark lighting	Das et al., (2020)
	Arterial roads	Boggs et al., (2020)

	Ramp or slip lane	S. Lee et al., (2023)
	Fixed objects	P. Liu et al., (2024)

5.3 Proactive Safety Analysis of Mixed Traffic

A. Key Scenarios

Three key scenarios were investigated in the mixed traffic in existing studies: (1) Car-following scenario; (2) Lane-changing scenario; and (3) Car-passing scenario. Fig. 5.3.1 presents these three scenarios.

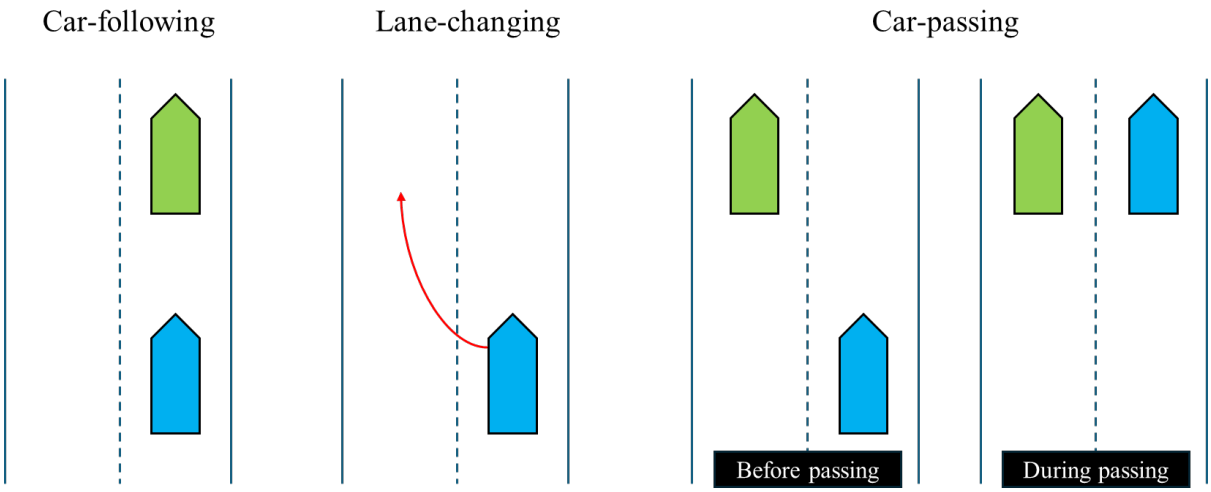


Figure 5.3.1 Three key scenarios in mixed traffic: Car-following, Lane-changing, and Car-passing

As a vehicle's longitudinal movement in the surface transportation system, the car-following scenario was the most common and the most representative in the traffic safety analysis, typically including a leading vehicle and a following vehicle on the road. In the mixed traffic domain, existing studies tried to analyze the car-following characteristics of HV-following-AV, HV-following-HV, and AV-following-HV, depending on different research purposes (e.g., Huang et al., 2022; Wen et al., 2022).

As one common scenario that involved the lateral movement of the vehicle, the lane-changing scenario usually involves complex interactions between the ego vehicle and other vehicles or road users on the adjacent lane, which was critical to mixed traffic safety. Existing studies categorized the lane-changing scenario into two types. i.e., mandatory lane changing and discretionary lane changing (Yang and Koutsopoulos, 1996). Mandatory lane changing is a required task and must be conducted to reach a specific destination while discretionary lane changing is voluntary and usually carried out to improve the current driving conditions. Some studies have explored discretionary lane changing given its importance in mixed traffic safety (e.g., Ali et al., 2024; Wen et al., 2023).

The car passing scenario mainly describes the process where a vehicle is passing another vehicle from the adjacent lane, which typically happens when a vehicle is trying to over-take

another vehicle (e.g., Huang et al., 2022). For the approaches used for mixed traffic behavioral analysis, please refer to Chapter 2 for more information.

B. Surrogate Safety Measures (SSM) and Metrics

Although the crash analysis contributed a lot of valuable information to mixed traffic safety, the crashes were still rare events and thus distributed in a very sparse manner during the testing and deployment of AVs in mixed traffic. For mixed traffic safety, it would take a long time for AV safety impacts to be revealed in real-world crash data. Therefore, evaluating mixed traffic safety based on historical crash data is always post-hoc. To address this issue, SSM derived from traffic conflicts was proposed, as traffic conflicts were more frequent and can be predictive of crashes. Typically, traffic conflicts in mixed traffic were observable non-crash events, in which the interactions of HVs, AVs, and other road users construct a risk of collision if these road users continue to move in the original trajectories (Wang et al., 2021). According to Tarko (2018), there are two qualifying criteria for SSM: (1) it should be derived from traffic conflicts which are directly linked to crashes, and (2) the relationship between traffic conflicts and the related potential crash frequency and/or severity can be quantified by some practical methods. SSM acted as the important basis for the proactive safety analysis of mixed traffic.

The SSM metrics used by previous studies could be categorized into three categories, which include time-based SSM (e.g., time to collision (TTC), time-exposed TTC, time-integrated TTC, time headway), deceleration-based SSM (e.g., deceleration rate to avoid the crash (DRAC), crash potential index (CPI), rear-end collision risk index (RCRI)), and energy-based SSM (e.g., DeltaV, conflict severity, crash index, conflict index) (Wang et al., 2021). Interested readers could refer to Wang et al. (2021)for a more comprehensive review of these SSM metrics.

However, most existing studies using SSM to evaluate mixed traffic safety were based on simulation (e.g., El-Hansali et al., 2021; Morando et al., 2018; Tafidis & Pirdavani, 2023), which were out of the scope of this chapter, thus we only included several studies that fitted our scope in the following sections.

C. Major Findings

(1) Findings from Experimental Study

In terms of experimental studies, some existing studies found that AVs can enhance mixed traffic safety. For example, Wei & Shao (2024) investigated the effects of AVs on human drivers' following behaviors through a driving simulator study, in which they found that, compared to following conventional human-driven vehicles, drivers exhibited less driving volatility in speed and acceleration and longer TTC when following AVs. Through a field experiment, Mahdinia et al. (2021) found that AVs in mixed traffic streams can induce behavioral changes in conventional vehicle drivers, with some beneficial effects on safety (i.e., lower driving volatility and higher TTC when following an AV) and the environment (i.e., consume less fuel and produce fewer emissions when following an AV).

Another experimental study highlighted the potential influence of drivers' subjective differences. Zhao et al. (2020) also investigated the differences between HV-following-HV and HV-following-AV using a field experiment, and they found that different drivers exhibit different behaviors in following-AV vs. following-HV: some are AV-believers, some are AV-skeptics, and the others are insensitive. And there was no significant difference between following a lead AV and following a lead HV, which indicated that drivers' response to the lead vehicle depends on their subjective trusts on AV technologies rather than the actual driving behavior.

(2) Findings from analysis of real-world data

In terms of analysis of real-world data, in line with the findings from experimental studies, most studies found that human drivers interacted with AVs more safely compared to when interacted with HVs. Many studies were conducted based on the Waymo Open Dataset. For example, Huang et al. (2022) explored human drivers' interactions with AVs in two types of events on highways, i.e., car-following events and car-passing events. They found that human drivers tended to keep a larger safety margin with increasing speed regardless of the types of vehicles they interacted with, by keeping a larger gap distance, and a larger TTC to the lead vehicle in car-following events. At the same time, drivers kept a larger lateral distance to AVs in car passing events regardless of the lead vehicle's speed. Similarly, by using the Waymo Open Dataset, Wen et al. (2022) characterized human drivers' following behaviors and compared HV-following-HV with HV-following-AV in terms of several safety metrics (e.g., TTC), they found that human drivers had lower driving volatility in terms of velocity and acceleration/deceleration, smaller time headways and higher TTC. Hu et al. (2023) also tried to characterize the empirical car-following behaviors of AVs and compare AVs' car following behaviors with HVs' car following behaviors (Hu et al., 2023). They found that AVs were much safer than HVs based on several surrogate safety measures, as time headways and jam spacings of the AVs were significantly larger than HVs. The authors also noted that the current AV behaved in a conservative way to ensure its safety at the cost of efficiency. Ali et al. (2024) investigated the discretionary lane-changing execution behavior of AVs and compared AVs' behavior with HVs, and they found that AVs maintain larger lead and lag gaps, longer discretionary lane-changing execution time, and lower acceleration variation than HVs, which means that AV presented safer discretionary lane-changing behavior compared to HVs (Ali et al., 2024). Based on the Lyft level-5 dataset, Li et al. (2023) also compared the operation behaviors of HV when following different leading vehicles, i.e., HV-following-AV and HV-following-HV (Li et al., 2023). They found that mixed traffic safety had been enhanced after the introduction of AV, which was evidenced by the changes in HV behaviors (i.e., less aggressive, larger TTC).

To summarize, existing studies using real-world data revealed that human drivers seem to interact with AVs in a generally safer way, compared to interacting with HVs. However, more research is still needed as the data used in existing studies were still limited and might be biased in representing human drivers' behaviors in mixed traffic.

5.4 Potential Research Directions for Improving Mixed Traffic Safety

As suggested by findings from crash analysis and behavioral analysis in existing empirical studies, we proposed several potential research directions for improving mixed traffic safety as follows:

- AVs need to be improved in terms of detecting and warning human drivers of the following vehicles approaching from behind to avoid rear-end collisions. For example, AVs could communicate the current status and intention with other HVs through external human-machine interfaces (eHMI) (e.g., Dey et al., 2021; Papakostopoulos et al., 2021; Yan, Huang, Xie, et al., 2023). Until now, there were no established standards on how to design the eHMI for AVs and what information should the eHMI include, future research may explore the effectiveness of different eHMI designs (e.g., appearance, included information).
- To reduce injury crashes, the surface transportation systems should improve the roadway infrastructures to better support AVs. For example, one possible solution for avoiding human drivers' rear-ended AVs could be to separate AVs from HVs by using AV-only lanes (Yu et al., 2019). However, there might be a trade-off between safety and efficiency, future research could explore the effects of different roadway infrastructures on the safety and efficiency of the whole transportation system.
- The risky factors of AV crashes identified from existing studies could be used in several ways: (a) To develop safety-critical testing scenarios for efficient and reasonable testing for future driving automation (Kibalama et al., 2022; Lee et al., 2024; Song et al., 2021); (b) To help develop vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) technologies (Harding et al., 2014); and (c) To guide the design and optimization of AV algorithms in specific scenarios (Sharma et al., 2021).
- Inspired by drone-based and computer vision-based techniques (Zheng et al., 2024), we highly recommend research efforts on collecting the trajectory data that includes the interaction between AVs and HVs on publicly open roads and analyzing the mixed traffic safety through SSM.

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