Analysis of Intelligent Vehicle Technologies to Improve Vulnerable Road Users Safety at Signalized Intersections

July 2022

A Research Report from the National Center for Sustainable Transportation

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16. Abstract
This project aims to know how the Intelligent Vehicle Technologies (IVT) can improve Vulnerable Road Users' (VRU) safety in different environments and conditions (e.g., sight distance and traffic flow) at signalized intersections. For the statistical analysis on historical aggregate crash data, the project studied risk factors on crash injury severity for VRU-related crashes at signalized intersections in California cities. The researchers summarize seven critical crash types for the micro-level traffic safety simulation. For the traffic safety simulation part, it is found that Intersection Safety (INS) is empowered to be the most efficient technology to significantly reduce average collision counts for passenger cars under all seven collision types of interest. Blind Spot Detection (BSD) has the most minimal effects on those types. The safety improvement of VRU Beacon Systems (VBS) and Bicycle/Pedestrian to Vehicle Communication (BPTV) are between INS and BSD. Results show that under a certain threshold of sight distance, IVT can significantly reduce the collision probability and IVT can still improve safety under good sight condition if collisions happen in front of vehicles. In the end, the project conducted sensitive analyses of sight distance and traffic volume. For some collision types, INS and BPTV can only reduce ~50% of collision at extremely high traffic volume conditions.

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Intelligent Vehicle Technologies, Vulnerable Road User, Traffic Safety, Micro Simulation

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Acronym	Definition
BPTV	Bicycle/Pedestrian to Vehicle Communication
BSD	Blind Spot Detection
INS	Intersection Safety
IVT	Intelligent Vehicle Technology
MNL	Multinomial Logit
OTS	Office of Traffic Safety
OR	Odds ratio
PET	Post encroachment time
SafeTREC	Safe Transportation Research and Education Center
SWITRS	Statewide Integrated Traffic Records System
SSM	Surrogate safety measures
TIMS	Transportation Injury Mapping System
TTC	Time to collision
VBS	Vulnerable Road User Beacon Systems
VRU	Vulnerable Road User
VTB	Vehicle to Bicycle Communication

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EXECUTIVE SUMMARY

As advanced vehicle technologies enter transportation systems, e.g., sensor technologies in personal vehicles, freight trucks, and other users (e.g., vulnerable road users, VRUs), we have more reliable solutions to improve safety of all traffic agents, especially VRUs. Moreover, it is reasonable to assume that the incoming 5G Era would help mitigate telecommunication challenges for some of these advanced intelligent vehicle technologies (IVTs). Therefore, we need to know how these IVTs can improve VRU safety in different environments and conditions (e.g., sight distance and traffic flow) at signalized intersections. Moreover, there are technical, operational, and financial differences between the various IVTs, and there are limited studies about their adoption rate on safety improvement. To address these knowledge gaps, we combine aggregate historical crash data analysis and microscopic traffic simulation to examine the safety impacts of four IVTs. Most importantly, we develop an empirical microsimulation tool to quantify the safety impacts of these IVTs.

For the statistical analysis on historical aggregate crash data, we study the risk factors on crash injury severity for VRU-related crashes at signalized intersections in cities in California. Data from the cities with high crash rankings given by the Office of Traffic Safety (OTS) were compiled using a five-year statewide dataset from the California Statewide Integrated Traffic Records System (SWITRS). Multinomial logit (MNL) models were performed on injury severity, and interaction terms with movements preceding collision were also modeled to identify typical collision types for crashes involving pedestrians and bicyclists. The differences in factors in the scenario models were also analyzed for different VRU-driver movement combinations. The research yields three impactful results: 1) The severity of pedestrian accidents in rainy weather overall is unlikely to become more serious, and the odds ratios (OR) of the severity of bicycle accidents also do not change significantly. Compared to VRU crashes where through traffic vehicles were involved, the OR of severe and fatal crashes in right-turn cases decrease, showing that turning movements are less likely to be associated with fatal crashes. 2) The OR of severe or fatal accidents between pedestrians and bicycles significantly increases at night (with street lights) compared to daytime, which means that the lack of light conditions increases the probability of a severe VRU crash. 3) In terms of demographics of crash parties, there is a significant correlation with males at-fault in accidents with increased severity of VRU injuries, and VRU crashes in the high age group are more likely to be fatal. Most importantly, we summarize seven critical crash types for the following micro-level traffic safety simulation.

For the traffic safety simulation part, we mainly complete two tasks, including 1) to amend and modify the parameter setting of the junction model of the Simulation of Urban Mobility (SUMO) engine to simulate the real-world vision acuity and wireless communication process which is essential in IVTs; 2) to implement crash simulation by using the amended parameters of ITVs. What is innovative of the simulation tool is that it has taken human and environmental

factors in the real world such as visual acuity, weather, and the inevitable wireless communication error of the IVTs. The simulation tool is then contributing to the methodology of crash simulation by providing a new perspective to simulate crashes in the software which was supposed to be accident-free in previous studies. Through the simulation we find that Intersection Safety (INS) is empowered to be the most efficient technology to significantly reduce average collision counts for passenger cars under all seven collision types of interest. Blind Spot Detection (BSD) has the most minimal effects on those types. The safety improvement of VRU Beacon Systems (VBS) and Bicycle/Pedestrian to Vehicle Communication (BPTV) are between INS and BSD. If we compare different type of collisions, all IVT can reduce the collision probability more when the collisions happen as vehicles make turns (left and right). In addition, the safety impacts of one of the IVT are also different between passenger cars and trucks. VBS, BPTV, and INS are more efficient to reduce collision happening right in front of trucks since there are blind spots in front of trucks. In the end, we conduct sensitive analyses of sight distance and traffic volume on the safety impacts of four IVT. Results show that under a certain threshold of sight distance, IVT can significantly reduce the collision probability and IVT can still improve safety under good sight condition if collisions happen in front of vehicles. In the sensitivity test for traffic volume, we set four different level of traffic volume, i.e., low, medium, high, and extremely high. INS and BPTV can reduce 100% collisions from medium to extremely high traffic conditions for most collision types simulated. However, for some collision type, INS and BPTV can only reduce around 50% of collision at extremely high traffic volume conditions.

Over, our research develops a novel traffic safety evaluation framework, which is based on mirroring real-world vision acuity and IVT implementation. Our simulation results also find the best working condition (e.g., sight distance, traffic volume, and intersection shape) for four different IVT. The analysis of these technologies can help both public and related stakeholders to better understand how different IVT will improve the safety of cyclists and pedestrians under various conditions at intersections. Thus, this research will eventually promote the adoption of IVT in future transportation scenarios. The research could inform State agencies such as Caltrans, and local (metropolitan) planning organizations about how to develop various IVT and would have implications for improving the mobility of people and goods.

Introduction

Fatalities from motor vehicle crashes lead all accident deaths in the US, with a great economic loss (NHTSA 2018). There were 6,205 pedestrians and 843 bicyclists killed in 2019 and approximately 76,000 pedestrians and 49,000 bicyclists injured in motor vehicle crashes on public roadways in the U.S. (NHTSA 2017). Moreover, in California, 27.2% (982) of all reported crash-related fatalities were VRU ("Pedestrians and Bicyclists" n.d.). In this research, the term VRU is used mainly to describe road users unprotected by an outside shield, which mainly contain pedestrians and bicyclists.

Often, crashes involving VRU occur at intersections. There are four main categories factors influencing crashes between vehicles and VRU: crash parties' demographics, drivers' behavior, intersection condition, and weather. Habibovic and Davidsson (2012) used the SafetyNet Accident Causation System (SNACS) to create an aggregated causation chart for VRU as well as for different intersection types, injury severity levels, and trajectory types. They found that 30% of VRU had visual obstructions before the crashes, and many would have benefited from active safety systems to avoid misunderstanding the traffic conditions or making inadequate actions. Besides crashes at intersections, Robartes and Chen (2017) analyzed general crashes between vehicles and cyclists. Among all factors, the intoxication of both drivers and cyclists could hugely influence the severity of cyclists' injuries. Additionally, other factors, such as bicycle and automobile speeds, obscured automobile driver vision, vehicle types (SUV, truck, and van), and road design, would increase the probability of more severe bicyclist injuries.

Silla et al. (2017) further quantitatively analyzed the influence of five intelligent transport systems in terms of decreasing motor vehicle VRU related crashes. Among all the systems examined, Bicycle to Vehicle Communication (B2V) shows the highest impact on safety since it can cover all potential accident conditions. They also highlight the importance of technology adoption rates as a critical factor for their safety improvement potential. Patil (2016) and Ellen, Pace, and Yoon (2015) studied the adaptation of Vehicle to Bicycle (V2B) communication technologies in the real world. Their study shows that cyclists are willing to equip their bicycles with specific technology considering the potential improvement of personal safety.

As reflected by the literature, several sensor technologies in personal vehicles, freight trucks, and other users (e.g., VRU) could help improve safety. Moreover, it is reasonable to assume that the incoming 5G Era would help mitigate telecommunication challenges for some of these advanced IVTs. Therefore, we need to know how these IVTs will affect VRUs' safety in different environmental and system conditions (e.g., sight distance and traffic flow) at signalized intersections. Moreover, there are technical, operational, and financial differences between the various IVTs, and there are limited studies about their adoption rate on safety improvement. To address these knowledge gaps, we combine aggregate historical crash data analysis and micro transportation simulation to examine the safety impacts of four different IVTs on VRUs' safety. Most importantly, we develop an empirical microsimulation tool to quantify the safety impacts of these IVTs on VRUs. The microsimulation tool has taken human and environmental factors in the real world such as visual acuity, weather and the inevitable wireless communication error of the IVTs, and is then contributing to the methodology of crash simulation by providing a new perspective to simulate crashes in the software which was supposed to be accident-free.

Literature Review

This section summarizes current related research from three aspects: 1) studies on IVTs; 2) VRU safety analysis at intersections; and 3) traffic simulation as a safety evaluation tool.

Related Work on IVTs

Generally, IVTs cover a wide range of technologies based on a variety of origins and innovations that require research from different disciplines. Specifically, the IVTs studied in this research refer to 1) Blind Spot Detection (BSD), 2) VRU Beacon System (VBS), 3) Bicycle/Pedestrian to Vehicle Communication (BPTV), and 4) Intersection Safety (INS). With the consideration of the undermentioned four types of IVTs, we can summarize the previous research and studies into four aspects, namely vision extension, sensing, communication and inference ability. Table 1 shows the review of the four IVT and the summary of their corresponding theory, advantages and disadvantages from previous research.

Studies on VRU Safety at Intersections

In terms of traffic safety evaluation and research at intersections, most of the previous research is divided into three categories. The first is to use historical surveys, traffic accident reports and other data for macro statistical modeling, such as logit models. The second is to use microscopic traffic simulation to study safety measures such as time to collision (TTC) and post encroachment time (PET) to evaluate traffic safety at intersections. The third is to invite volunteers to conduct driving simulator experiments to obtain measured data for research. Table 2 shows the review of these three categories of related work regarding intersection traffic safety.

Traffic Simulation as a Safety Evaluation Tool

Traffic simulation, as quantitative tools that use complex software whose development can be facilitated by considering a multi-agent approach (Doniec et al. 2008), is able to reproduce real traffic phenomena using a variety of models, such as car-following models, behavior/mental models and other micro level simulation models. As stated in Table 2, the previous research and analysis of traffic safety is mostly based on statistical models that use macro level crash data. However, the dependence on historical and empirical data limits the ability to consider the risks connected with many risky traffic scenarios such as those that would lead to potential crashes (Astarita et al. 2021), and could not provide quantitative results that can predict the safety trends when new scenarios are set in the future.

Amid the development and iterations of different traffic simulation software, the burgeoning and improvements of different traffic simulation models showcase the essence of maturity of simulation models. For one thing, in 1997, Lieberman and Rathi proposed a highway traffic simulation model using car-following models, which include differential equations that are obtained empirically. Since then, most of the microscopic simulations that consider each traffic agent (vehicle, bicycle and pedestrian) use various car-following models to allow each traffic agent to move and cross the intersections in a virtual queue. For another thing, behavioral approaches has also emerged to serve as useful models that consider traffic as an emerging phenomenon resulting from actions and interactions of the various traffic agents (Doniec et al. 2008; Heinovski et al. 2019).

Considering the context of our project, behavioral models plainly manifest the interactions between vehicles and VRU in microscopic simulation, which is a preferred approach for the project. Kitajima et al. (2019) developed a multi-agent simulation model that combines the use of these two approaches. Innovatively, the authors define the driving process as a three-stage (perception & recognition, decision making, and action) one and integrate driver diversity and error models into the process. This hybrid approach significantly reduces the complexity of a scheme of behavioral models only and utilize the traditional car-following models.

Among the three stages of a driving process, perception and recognition serve as the most important part as the results of perception and recognition are the basis of decision making. Perceptual range, which has been demonstrated to influence the relative speed of self-motion by visual information (Larish and Flach 1990), works as a very important part for vehicle perception phase throughout the driving process, and it has different definitions and coverages with or without the introduction of IVT. In manual driving scenarios, perceptual range mostly count for visual information obtained by a driver, which is called field of view, line of sight and visual acuity by some studies (Kitajima et al. 2019; Coeckelbergh et al. 2002; Gattis and Low 1998; Hussain et al. 2020). Under this scenario, two parameters are critical that determine the visual field: distance and angle of view. Studies from Japan suggest that view distance usually ranges from 80 to 120 m and view angle ranges from 120 to 160 degrees (Kitajima et al. 2019). Gattis and Low (1998) suggest the maximum horizontal head movement to be approximately 109 degrees, and an individual cannot perceive vehicle movement much beyond 244 m (800 ft) or discern detail beyond 427 m (1,400 ft). It is also pointed out that view angle may decrease as the driving speed increases, resulting in 120° at 30 km/h and only 45° at 100 km/h (Djamel et al. 2020). Wu et al. (2013) have studied the rear-view distance and angle regarding blind spots and proposed a blind spot detection system defining that the horizontal view angle between the cameras and the body of the car is 75.2°, and that the detection zone covers 20 m behind the camera and a 4 m width on both sides.

It is necessary not only to implement the existing results of studies as the basis of our simulation model, but also take the effects of IVT on perceptual range into account. Although the literature presents the themes of visual acuity in a variety of contexts, this project primarily focus on their application to microscopic simulation as well as the effects of IVTs.

Table 1. Review of previous research of the four IVT.

Intelligent vehicle technology			Theory	Advantage	Disadvantage	Relevant findings from experiments
Blind spot detection (BSD)	Sensing system (detection)	Camera-based system	Image processing & object detection (Z., Hassan 2020)	1. Fast and real-time detection for optical flow processing 2. Extra safety information with panoramic camera (Z., Hassan 2020)	1. Insufficient or distorted images for object extraction (Z., Hassan 2020) 2. Sensitive under bad weather conditions (Hyun, Jin, and Lee 2017) 3. Requires accurate algorithm (Z., Hassan 2020)	1. Detection rate of pedestrians: 77%. 2. Can reduce 5% of light vehicle-cyclist accidents and 13% of all vehicle-cyclist accidents. 3. Overreliance by the VRU is assumed to apply to 0–1% of blind spot accidents. (Silla, Leden, et al. 2017)
		Radar-based system	Radar detection / short distance measurement (Z., Hassan 2020)	1. Fast operation and short processing time (Z., Hassan 2020) 2. Short distance measurement (Z., Hassan 2020) 3. Can provide the position and velocity of the target object (Hyun, Jin, and Lee 2017)	1. Smaller field of view (Hyun, Jin, and Lee 2017) 2. Unable to detect object type (Hyun, Jin, and Lee 2017)	
	Inference ability (ability to alert potential collision)	Vision-based	Optical flow analysis or pattern recognition (Hyun, Jin, and Lee 2017)	1. Superior angular resolution (de La Garanderie, Abarghouei, and Breckon 2018) 2. Object classification	1. Requires explicit annotated training datasets (de La Garanderie, Abarghouei, and Breckon 2018) 2. Hard detection at nightime or under bad weather condition	

Intelligent vehicle technology			Theory	Advantage	Disadvantage	Relevant findings from experiments
		Radar-based	Uses triangular waveform to obtain relative velocity and distance; The key boundary point is captured; System will determine objects. (G. Liu, Wang, and Zou 2017)	Accurate detection and prediction; Does not require training datasets	No object categorization	
Bicycle/Pedestrian to vehicle communication (BPTV) and intersection safety (INS)	Sensing system (detection)	Radars (RSU-based)	Captures a list of reflection-points (range, velocity, angle, etc.) (Milch and Behrens 2001)	Fast reaction and processing; Long detection range; Low data rate requirement (Barnett et al. 2020)	Radio signal ranging has poorer accuracy and resolution. (Barnett et al. 2020)	1. In 30–70% of accidents, at least one of the parties involved has the system switched off. 2. The effectiveness is estimated as 50–60%. 3. A reduction with 0.5% of all intersection crashes. (Silla, Leden, et al. 2017) 4. 79GHz radar can give position accuracy at a centimeter level. (W. Liu, Muramatsu, and Okubo 2018)

Intelligent vehicle technology			Theory	Advantage	Disadvantage	Relevant findings from experiments
		GPS	Collects position info (static) w/ position devices embedded in vehicles and phones, provide absolute coordinate (W. Liu, Muramatsu, and Okubo 2018)	Simple implementation; Low cost (no additional devices required).	Apps and algorithms needed; Large positioning error (Jenkins, Duggan, and Negri 2017); Always-on can be too energy-intensive (Li et al. 2018)	GPS was frequently accurate to within 3-4 meters despite an average reported error of 17.5 meters (Jenkins, Duggan, and Negri 2017). GPS error on lateral direction is larger than that of longitudinal. GPS error in distance is approximately 10 m (Anaya et al. 2014).
		Wireless sensor (2.4 GHz)	Four wireless receivers on a single vehicle to send and receive the signals. (Hisaka and Kamijo 2011)			To achieve e.g., 80% of PDR, the distance needs to be smaller than 130m (resp. 305 m) for low speed (resp. high). Information exchange distance: 39.5, 52.3, and 72.0 m, at 30, 50, 80 km/h, respectively. (Anaya et al. 2014)
		Tag-based (RSU-based) (Dasanayaka et al. 2020)	Information is communicated using transmitters and receivers via RFID.	Low energy use; Can function even in the NLOS or bad-weather situations;	Communication radius is small; Limited information is communicated between vehicles and VRU Lack of data resulting in difficult implementation of collision avoidance applications	

Intelligent vehicle technology			Theory	Advantage	Disadvantage	Relevant findings from experiments
		Lidars (RSU-based)	Measures distances with laser light and collects a real-time set of reflection points	Lidar typically has better lateral resolution compared to radars; Long detection range (Barnett et al. 2020); Power saving (Zhao et al. 2019)	Performance degrades in adverse weather conditions (Barnett et al. 2020); Needs clustering algorithm	Approximately an accuracy of 95% can be reached within 30m detection range (in one direction)
		Cameras (vision-based) (RSU-based)	Uses image identification to detect VRU		Limited by the FOV; performance degrades sharply when the visibility is occluded by other obstacles (W. Liu, Muramatsu, and Okubo 2018). Requires much more processing and computing power; expensive; night vision problem (high ISO); cannot cover a much wider detection range (Zhao et al. 2019). High data rates required for sharing raw sensor data (Zheng et al. 2020). Rely heavily on the quality of training datasets (Barnett et al. 2020). Works poorly in dim lighting	
		On-board camera	Embedded cameras on vehicle can detect VRU and its movement	1. Cover larger areas than fixed cameras. 2. Low cost	Need more sophisticated algorithms to reach similar performance Can only detect the environment around the vehicle	The detection overlap rate ranges from 81.5% to 90.7%, with an average overlap rate of 86.9%. (Ke et al. 2017)

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Intelligent vehicle technology			Theory	Advantage	Disadvantage	Relevant findings from experiments
	Communication system	DSRC (5.9GHz band with 75MHz spectrum)	Able to share position, speed and direction of VRU which are collected by the sensing system. (Yoon, Pace, and Ellen, n.d.; Jenkins, Duggan, and Negri 2017)	Mature communication technology w/ high penetration rate; Higher PDR, more efficient than WiFi (Fitah et al. 2018)	High latency time; Cannot support high transmission rate	Detection of bicyclists using DSRC communication appears to be easier than relying only on sensor-based detection techniques (Patil 2016b); The average deviation between the radar measurements and the 700MHz communication data is about 7.5 m. (W. Liu, Muramatsu, and Okubo 2018)
		WiFi communication (2.4 / 5 / 5.8 GHz)		Mature communication technology w/ high penetration rate;	If the signal is blocked by the human body, the communications distance would be significantly shorter. High latency time; Performance deteriorates w/ the increase of traffic (Fitah et al. 2018)	The average delay of the IEEE 802.11p is lower than the delay of the IEEE 802.11a in highway and residential scenarios. (Fitah et al. 2018)
		4G LTE / 5G mmWave		Higher communication speed; Can transmit real-time data with high resolution (Zheng et al. 2020)	Low penetration rates; Requires dense BS deployment	A dense BS deployment, with an average distance between BSs of 50 m, and heavy traffic conditions were considered, most of the points in the map are above 1 Gbps. (Zheng et al. 2020)

Intelligent vehicle technology			Theory	Advantage	Disadvantage	Relevant findings from experiments
	Inference ability (ability to alert potential collision)	Collision point estimation	Calculates the projected space coordination of collision point based on trajectories of both entities.	Simple to implement	Does not consider the impact of speed range	
		Surrogate measures estimation	Uses TTC, PET, etc. to predict the underlying collision and triggers alert when the indicator is under a preset threshold.	Widely adopted method; Ensures safety against from potential conflicts to fatal crashes by setting different thresholds	Straight line movement assumption	
		Probability of collision	Calculates collision probability by using trajectories and the collision speed range and the speed distribution model of vehicles.	An improved version of surrogate-measures-based algorithms; Considers VRU movement uncertainty	Ambiguous threshold which is unable to ensure safety	

Intelligent vehicle technology		Theory	Advantage	Disadvantage	Relevant findings from experiments
VRU beacon system (VBS)	Bluetooth beacons	Beacons are transmitted every 100 m. (Dhondge et al. 2014)	Has a range of transmission of at least 40 meters; Suitable for high-speed roads. (Barnett et al. 2020)	Higher transmission rates lead to high channel burden which may lead to false or missing detection. (“Performance and Channel Load Evaluation for Contextual Pedestrian-to-Vehicle Transmissions | Proceedings of the First ACM International Workshop on Smart, Autonomous, and Connected Vehicular Systems and Services” n.d.)	The road exposure of cyclists is expected to increase by 0.8–1.8% with use of VBS. The range for the Aps (access points) is ~50 m (Silla, Leden, et al. 2017); With WiFiHonk a VRU can be safely alerted of a collision in a timely manner even for high speeds (60 mph) (Dhondge et al. 2014); The standard deviation for position error has to be smaller than 0.4m (Bachmann, Morold, and David 2020); Approach using Bluetooth demonstrated the use of RSSI localization with a particle filter, resulting in a measurement error of 0.427±0.229m (Barnett et al. 2020).

Table 2. Review of related work regarding VRU and traffic safety at intersections

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Robartes and Donna Chen 2018	**Purpose**: Designed, distributed, and analyzed a **bicycle safety and attitude survey**, to characterize the state of bicycling conditions in Virginia and reveal factors that impact bicycling safety. This research is one attempt to address gaps in bicycle data in sources such as police crash reports.	**Methods:** A **survey** was developed and deployed to enhance the quality and quantity of available bicycle safety data in Virginia. An **MNL modeling** was then performed. The survey captures a variety of data through questions on travel history, safety, past bicycle crashes, and demographics, bicyclist attitudes and perceptions of safety as well as bicycle crash histories of respondents. A total of 686 survey responses were recorded, only 459 people (66.9%) completed the survey. Weights were utilized to better represent the bicycling community in Virginia.	**Results:** Very high levels of under-reporting of bicycle crashes, with only 12% of the crashes recorded in this survey reported to police. Lack of knowledge concerning bicycle laws is associated with lower levels of cycling confidence. Count model results predict that bicyclists who stop completely at traffic signals are **40% less likely** to be involved in crashes compared to counterparts who sometimes stop at signals. **Conclusions:** Among crashes experienced by survey respondents, 12% of the crashes were reported to the police. Among bicycle crashes involving automobiles, 66% of minor injury crashes and 19% of severe injury crashes were not reported. This result underscores the importance of education of bicycle laws in building cycling confidence, and thereby potentially encouraging more people to start biking.	**Limitations:** The survey sample may be biased toward highly active bicyclists who are generally more confident riders. Lacks a strategy for locating and contacting more casual riders to get a more balanced survey sample	**Comments:** Modeling results provide findings to support local policymaking and legislation. Discloses the underreported VRU accidents and how Helmet use, stopping completely at intersection and light/reflective use might affect VRU crash rates at intersections. The exact parameters are not robust since the survey involves biased sample.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Silla, Rämä, et al. 2017	**Purpose**: ITS needs to specifically address VRU as an integrated element of the traffic system. Presents a quantitative safety impact assessment of five systems that were estimated to have high potential to improve the safety of cyclists: BSD, B2V, INS, PCDS + EBR and VBS.	**Data:** The CARE database was chosen for the analysis due to it covering accidents on a European-wide level. Some were taken from the national statistics. The countries were grouped in three clusters based on the prevalent safety situation in each country. Average value imputation was performed to replace the missing values on background variables, such as road type and weather condition. **Method:** 1) system description of anticipated driver/VRU reactions; 2) description of behavior and safety effects; 3) estimate of effects by different mechanisms, in terms of % increase/decrease of relevant accidents. Stepwise safety assessments among both internal and external **experts** were made with the **output of an estimate of effectiveness (low, medium and high)**. 4) A separate mobility assessment study under the framework of Johnasson's study; 5) Estimation of the penetration rates for the systems; 6) Estimation of accident trends for each cluster; and 7) Calculation of effects, which were applied to the EU-28 road accident data.	**Results:** The current best detection rate of pedestrians in the blind spot of vehicles is 77%. For cyclists, no figure has been found. The main results of the assessment showed that all investigated systems affect cyclist safety in a positive way by preventing fatalities and injuries. The estimates considering full penetration showed that the highest effects could be obtained by the implementation of Pedestrian and PCDS + EBR and B2V, whereas VBS had the lowest effect. B2V was estimated to have a relatively high impact on safety, due to the fact that it potentially addresses all accidents. The other three systems INS, BSD and VBS also show a significant potential to improve the safety of cyclists. Their effects are lower because they target specific situations (INS, BSD) or are limited in their effectiveness (VBS).	**Limitations:** Data uncertainty related to a) estimates of safety effects (they depend on the results of expert questionnaire and findings from the literature), b) accident data (for some systems we have better data for accident types the system aims to prevent than for some others), c) estimated accident trends, and d) estimated penetration rates. The results in this paper concern only fatalities because of under reporting data.	**Comment:** The database used in the research has the problem of underreporting, which makes the subjects of follow-up research biased from accidents to fatalities. The relative estimate obtained by Stepwise assessment is also lower than the actual situation.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Robartes and Chen 2017	**Purpose:** to identify the factors which contribute to injury severity of bicyclists in bicycle-automobile crashes	**Data:** Virginia police crash reports between 2010 and 2014. 3545 (96.4%) of the original VA DMV dataset are single automobile and bike crashes. **Method**: The authors preferred an ordered probit (OP) model. Actually, both MNL and OP models were considered, but the OP specification yields a better model fit. The response variable is the injury severity of the bicyclist in the crash.	**Results:** The speed at which the bicycle was traveling at the time of the crash affects the injury severity levels. Biking while inebriated doubles the probability of severe injury for the cyclist. Drunk drivers increase the fatality risk for cyclists more than any other factor studied. Divided and one-way roads to be safer for bicyclists, indicating that bike lanes can reduce conflict between automobiles and bicyclists. Roadway characteristics to be detrimental to the likelihood of severe injuries.	**Limitations:** This method introduces some subjectivity into the bicycle speed data. No injury, no apparent injury and minor/possible injury crashes are underrepresented in the distribution of crashes. Some specific variables, such as the injury severity of the bicyclist allow for bias and subjectivity. Approximately one-third of the cases were incorrectly coded.	**Comment:** The dataset used in the research has strong subjectivity, which has a great influence on the estimated parameters of the Ordered Probit model, and should be biased. We can only roughly accept the signs of the parameters, but the specific numbers should not be used in our simulations.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Habibovic and Davidsson 2012	**Purpose:** To develop a thorough understanding of crash causation mechanism. To identify crash causation mechanisms from the perspective of the VRU, and to explore the implications of these mechanisms for the development of active safety systems.	**Data:** The in-depth crash data were collected by multidisciplinary teams in the European project SafetyNet (Björkman et al., 2008) in the time period 2005–2008. The total data set consists of **995 crashes**, **180 of which are car-to-VRU crashes**. The data collect age, gender, and injury severity level of the pedestrians and bicyclists, along with the crash distribution according to weather conditions, light conditions, posted speed limits, and intersection type. **Method:** Presents the most common causation patterns identified from various aggregations of the 56 individual causation charts. Common is here defined as an element (a critical event, a contributing factor, or a link) that occurs more than five times. When comparing the aggregated charts, the element occurrence frequencies that exceed 15% are highlighted.	**Results:** the most common critical events: inadequate timing (premature action, no action and late action), distance, duration. Common contributing factor to precede the critical events: Faulty diagnosis, Inadequate plan, Observation missed. Visual obstructions were more frequent for bicyclists than pedestrians. Does not seem these two groups of VRU need separate treatment when it comes to active safety system development.	**Limitations:** The limited number of cases, which makes generalization difficult. Lack of geographical representation.	**Comment:** This paper fails to deliver consolidate results based on a large enough sample size. It does not incorporate the IVT in the causation study.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Mohsen Kamrani, Behram Wali, Asad J. Khattak, 2017	**Purpose:** This paper focuses on developing an analytic methodology to examine instantaneous driving behaviors at intersections and their variability, and explores how variability in driving can be mapped to historical safety outcomes such as crashes at specific locations The nature of extreme instantaneous driving behavior at intersections can be correlated with their crash history.	**Data:** the 2-month connected-vehicle data from the SPMD (). The SPMD collects BSMs that describe a vehicle's position and motion, its component status, and other relevant travel information. Data on 5 years of crashes (2011 to 2015) along with geometric factors and flows were extracted and linked to the LBV for each intersection. **Method**: First, the connected-vehicle data consisting of geocodes and longitudinal acceleration were cleaned. Crash data along with geometric elements (road design, AADT, intersection type, etc.) were collected on 116 intersections in Ann Arbor. To calculate LBV, the authors intended to use longitudinal and lateral accelerations. Uses coefficient of variation (CV) for quantifying the fluctuations in longitudinal acceleration and deceleration at each intersection. Poisson models, Poisson–gamma models (negative binomial), or both, are estimated depending on the mean and variance of crash data.	**Result:** the volatility of deceleration regardless of speed range is positively associated with crash frequency. Volatility at lower speeds is more a significant factor as compared with volatility at higher speeds. On average a 1% increase in CV_DH is associated with a 0.11 increase in crash frequency for all intersections and a 0.089 increase in crash frequency for signalized intersections. A one-log unit increase in major road AADT is associated with 2.69-, 6.57-, and 1.82-unit increases in crash frequency for all intersections, signalized intersections, and unsignalized intersections, respectively.	**Limitations:** the study could not incorporate lateral acceleration and deceleration in the estimate of intersection-specific volatility. Uses one month's data were used to explain 5-year average crashes.	**Comment:** Does not provide technical solution or mappings for interactions between vehicles and VRU, and does not have focuses on VRU related crashes.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Yue et al. 2020	**Purpose:** to investigate the influences variation, in vehicle-to-pedestrian crashes, regarding driver response and safety benefits in different pre-crash scenarios.	**Data:** the data was collected by the National Advanced Driving Simulator (NADS MiniSim). (three screens driving simulator) **Method**: 1) Driving scenario design three experimental scenarios based on two factors: failure to recognize ped's crossing intention, and failure to observe ped due to obstructed sight of view. In each scenario, the scenario objects were configured according to speeds and positions of the pedestrian and car, the position and type of obstruction, roadway features such as number of lanes and speed limit, etc. 2) Within-subjects experiments warning type (without/with P2V warning) was made as the within variable. Each participant was tested for all three scenarios. within-subjects repeated measurement analysis of variance (ANOVA) analysis. A correlated errors model was developed by adding a random effect from individual drivers.	**Result:** 1) the P2V warning was released **4s before the pedestrian entered the collision zone** - the average brake reaction time was reduced from 1.0 s to 0.025 s (averaged from three scenarios) 2) the P2V warning interacted with age, and it reduced brake reaction time more significantly for young drivers (1.04 s) than working-aged drivers (0.77 s), and it reduced brake reaction time more for drivers that had a crash/citation experience within the past five years (1.13 s) than for those who didn't (0.97 s) 3) mean deceleration increased more significantly for females (-5.59 m/s2) than males (-4.51 m/s2), and it increased more significantly for drivers who had a crash/citation in past five years (-5.83 m/s2) than those who didn't (-4.39 m/s2) 4) warning increased significantly for non-experienced drivers by 1.98 m/s2 the collision rate was reduced by 87.11%, 77.94% and 88.56% in the three scenarios	**Limitation:** only considered three scenarios regarding peds and didn't cover other types of pre-crash conditions. Did not specify scenarios involving time of day, vehicle type and intersections. The pedestrian trajectory was simplified in this study by using a fixed trajectory path.	**Comment:** useful findings for setting up parameters in P2V communication traffic simulation.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Heinovski et al. 2019	**Purpose:** details a methodology to record real bicycle mobility traces in a safe and controlled fashion. Employs Virtual Reality (VR) technology to let participants ride a real bicycle through a simulated 3D scenario featuring intersecting roads and cycleways with or without signage and/or blocking their Line-of-Sight (LOS). -> to investigate the impact of wireless warning systems on road user safety.	**Virtual Cycling Environment:** - open source (http://www.ccs-labs.org/software/vce/) - cyclists ride a virtual bicycle in a 3D virtual reality environment by interacting with a physical bicycle on a training stand - Foreign traffic (cars) and wireless networking are provided by the specialized simulators SUMO and Veins (Vehicles in Network Simulation) - the virtual bicycle can be synchronized with Veins in real-time, which in turn provides ambient traffic (then rendered into the environment of the virtual bicycle) and network communication simulation. **Experiments based on scenarios:** - consists of a central intersection of 4 orthogonal road legs, with specific settings on each lane/corner of the intersection. - 10 cyclists, each cyclist repeated each of the 3 scenarios 3 times for a total of 9 traces per cyclist. - Recorded traces as input for the simulation study. **Collision detection:** By modeling each vehicle as a polygon, constructed from its width and length, it is possible to detect colliding vehicles by using separating axis theorem	**Results:** If we use 1 Hz beaconing, the awareness time increases to 2942 ms and 4291 ms for the car and the bicycle, respectively. Two different beaconing rates: When changing the beaconing frequency to 10 Hz, we see an increase in the warning time by 470 ms and 289 ms (median) for the car and the bicycle, respectively. 10 Hz frequency and Car-to-bicycle is the setting of best performance (longest TTC)	**Limitation:** There are no interactive studies in combination with V2X communication.	**Comment:** Good example of SUMO and Veins simulation for us to follow, but it requires physical equipment and recruitment.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Ouni and Belloumi 2018	**Purpose:** The paper describes the spatio-temporal pattern of VRU collisions according to temporal scale such as (a.m. vs p.m. rush hours VRU collisions, working days vs non-working days VRU collisions, daytime vs nighttime VRU collisions) and to develop a multinomial logit model in order to study the contribution of several variables to VRU collisions severity.	**Data:** The data used here cover 13 years from January 1, 2001, to December 31, 2013, (1) Collisions data obtained from NOITDSRS in Tunisia, (2) Highways data obtained from ministry of equipment, housing and territorial development (MEHTD) in Tunisia **Method**: 1) Exploratory study: (Ripley's K-function coupled with KDE approach) analyze the spatial concentration of road crashes by identifying areas of spatial concentration of crashes. 2) a multinomial logit model (dep: injury severity) was applied in order to study the contribution of several variables to VRU injury severity.	**Results:** male VRU are associated with an increased risk of fatal accident ((OR = 1.52; 95%CI [0.15–0.69])) compared to female VRU. compared to other road functional class, crashes occurring in national highway have a higher proportion of serious injury ((OR = 2.94; 95%CI [0.34–1.78])) The average visibility was also found to be significant in the serious injury function and estimated to be associated with higher VRU injury severity ((OR = 1.33; 95%CI [0.21–0.55])) relative to clear visibility as reference category. The fine weather condition is a significant factor in the injury severity model and estimated to be associated with higher VRU injury severity relative to foggy weather as reference category.	**Limitations:** restricted to Center-East regions in Tunisia. Subjectivity of crash report data additional investigation is required between hot spots-based crash counts and a variety of geometric characteristics, roadway characteristics, traffic flow characteristics and spatial features along these sections.	
Alshehri, Eustace, and Hovey 2020	**Purpose:** to determine factors that contribute significantly to the crash severity of intersection-related crashes involving motor vehicles and VRU	**Data:** Traffic crash data for three years, from January 1, 2013, through December 31, 2015, were obtained from the Ohio Department of Public Safety (ODPS). **Method**: binary logistic regression (dep: Crash Severity). Stepwise logistic procedure to select variables	**Results:** Out of fifteen predictor variables that were tested in the model, only five were selected by the stepwise procedure. Five significant variables at the 90% confidence level tested in the current study are VRU-related, road contour, light condition, gender, and unit in error.	**Limitation:** The same subjectivity issue as mentioned. Did not discuss speed-related variables.	

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Wu, Ardiansyah, and Ye 2018	**Purpose:** This study seeks to develop a generalized evaluation scheme that can be used not only to assess the effectiveness of IMA on improving traffic safety at intersections but to facilitate comparisons across similar studies.	**Method**: The proposed evaluation scheme utilizes the concepts of traffic conflict in terms of time-to collision (TTC) as a crash surrogate. This approach avoids the issue of having insufficient crash frequency data for system evaluation. A relative risk (a/(a+b))/(c/(c+d)) is calculated for comparing the risk of with/without using the IMA. **Testing**: (See the appendix) This study applied the proposed evaluation scheme and reported the effectiveness of IMA on improving traffic safety in a field operation test (FOT). Seven test scenarios were conducted at 4 intersections, and a total of 40 participants were recruited to use the IMA for 6 months.	**Results**: It was estimated that IMA users have 26% fewer conflicts with TTC less than 5 s and have 15% fewer conflicts with TTC less than 4 s. However, the results vary across different sites and different definitions of conflicts in terms of TTC.	**Limitations:** Limited study time period and number of intersections Driver heterogeneity: the effects of driver attributes on the effectiveness of IMA are not reported in this study Driver adaptation Interaction between human factors, design of the IMA, and roadway attributes:	**Comment:** The paper provides a novel way to test the effectiveness of a new IVT.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Wang et al. 2019	**Purpose:** To propose a multivariate copula ordered probit approach to model the four crash indicators – injury severity, crash type, vehicle damage and driver error – to identify the factors contributing to intersection crash consequences and explore the potential correlations among them using different copula formulation and parameterization strategies.	**Data:** 2016–2017 intersection crash data collected from the Connecticut Crash Data Repository (CTCDR) and only two-vehicle crashes were considered. 20,917 intersection crashes were used. **Method**: 1) Ordered probit model 2) Multivariate copula model To identify the best model, four copula methodologies including the Frank, Clayton, Joe and Gumble copula models were tested and compared in this study. Factors are divided into four groups: driver characteristics, highway and traffic characteristics, environmental characteristics, and vehicle characteristics.	**Results:** 1) the injury severity, crash type, vehicle damage and driver error are significantly correlated due to the common observed and unobserved factors, and their correlation varies among different crashes. 2) The model estimation results identify twelve important factors contributing to the crash consequences among them. 3) The dependencies among the four indicators caused by the common unobserved factors are all positive for the crashes that occurred at stop-controlled intersections and four-leg intersections and the crashes with involved drivers younger than 25.	**Limitation:** - Subjectivity - The copula model results contain some variables that are counterintuitive to the findings, such as the effects of adverse weather conditions on injury severity.	**Comment:** Good practice of statistical modeling, with an understandable and easy-to-follow framework. Results in table 3 are not transplantable directly.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Munira, Sener, and Dai 2020	**Purpose:** the paper develops a multivariate spatial Poisson-lognormal model in a Bayesian framework to examine the significant factors influencing the different severity pedestrian crashes at 409 signalized intersections in the Austin area.	**Data and method:** 1) Crash data: The traffic crash data were taken from TxDOT's Crash Records Information System (CRIS) (TxDOT, 2016b). The data obtained included the disaggregated crash data for all locations within the study area, collected over 8 years (2011–2018). 2) Pedestrian exposure data: Short-duration count data from the City of Austin Transportation Department, and continuous count data from Eco-Counter. - a direct demand model was developed to estimate pedestrian volume in all crash locations based on the available count data. 3) Multivariate spatial Poisson-lognormal model: independent variables correlation check -> variable selection including different combinations -> final model	**Results:** - The relative risk of a fatal crash for pedestrians at signalized intersections increased by around 10 % with an increase of one standard deviation in the speed limit. - The relative risk of incapacitating injury crashes and non-incapacitating injury crashes increased by 3.4 % and 2.4 %, respectively, with an increase of one standard deviation of traffic volume (in 1000 vehicles per day). - - the presence of a bus stop decreased (by 31 %) the risk of incapacitating injury crashes but increased (by 32 %) the risk of non-incapacitating injury crashes for pedestrians.	**Limitation:** - the aggregation does not capture the temporal variations of the explanatory variables.	**Comment:** No sidewalk data available in CA, hard to follow the procedure. But the results are worth references.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Montella et al. 2020	**Purpose:** the paper aims at developing and validating a procedure to rank unsignalized urban intersections for safety improvement based on the evaluation of risk factors by road safety inspections. High risk intersections, where safety measures that can reduce crash frequency do exist, can be identified and ranked by the SI.	**Safety Index (SI) procedure** - SI = Exposure × Risk Index (related to vehicles and peds) - Incorporating 10 safety issues with 23 detailed safety issues (see Table 1 for details) **Data for validation**: Crash data were obtained from the FDOT Crash Analysis Reporting System for the period 2011-2014. A sample of eighty-nine urban intersections located in Orange County was used. AADT volumes were provided. **Method**: 1) empirical Bayes (EB) method is used for identifying sites as hotspots/ hazardous road locations / high-risk locations / accident-prone locations / black spots / priority investigation locations. 2) The procedure was tested by comparison of the SI scores and the EB safety estimates. 3) the procedure was tested also by comparison of the SI scores and PFI.	**Results:** The correlation between the SI scores and the EB estimates was highly significant both for vehicles (R2=0.66) and pedestrians (R2=0.58) as well as for the total crashes (R2=0.68). The results from the Spearman's rank-correlation analysis provided further validation for the SI indicating that ranking from the SI and the EB estimates agree at the 99.9% confidence level for vehicles (ρs=0.78), pedestrians (ρs=0.93), and total (ρs=0.93).	**Limitation:** Could be extended with reference to other network elements.	**Comment**: good method to follow, but it requires pedestrian counts estimation, which brings uncertainty for modeling.

Researchers	Purpose and/or Research Question	Data and/or Methods	Results, Conclusions	Limitations	Comments
Hasani et al. 2019	**Purpose:** This study aims to estimate pedestrian and bicyclist exposure and identify signalized intersections with highest risk for walking and bicycling within the city of San Diego.	**Method:** 1) Identifying the intersections for short-term video data collection. 2) Developing a vision-based intersection monitoring system to automatically detect, track, and count pedestrians and bicyclists. 3) Converting short-term counts to long-term counts collected at the selected intersections. 4) Conducting exposure modeling and risk quantification for walking and bicycling at signalized intersections. **Data:** - A total of 1522 signalized intersection was identified. - Short-term video data were collected by National Data and Surveying Services (NDS). - For every intersection, demographic characteristics, socioeconomic, and built environment variables were obtained by buffer analysis in ArcGIS. crash data involving pedestrians and bicyclists were obtained from the Statewide Integrated Traffic Records System (SWITRS).	**Quantified Risk** $Quantified\ Risk = \frac{C\ x\ N^k}{AADP\ (AADB) x\ D}$ $C = \sum_s N_s\ x\ C_s$ **Highlights**: Exposure analysis identified transportation network, population, traffic generator, and land use variables as statistically significant in estimating pedestrian and bicyclist volume.	**Limitation:** Requires video surveillance data for analysis. Cluster method hard to follow. Small sample size.	

Analysis Methods

To accomplish the objective of this project, there are two parts of experiments: aggregate statistical analysis and micro level traffic simulation. First, we analyze the features mainly causing crashes between VRU and vehicles at intersections. Based on the statistical regression, we summarize the features and influence of different IVT. Second, after the statistical analysis and IVT summary, we conduct a microsimulation analysis to study the influences of different IVT on typical crashes. In the second part analysis, i.e., traffic simulation, we quantify the safety improvements for VRU based on different penetration scenarios.

Historical Crash Data Modeling

Multinomial Logit (MNL) modeling with interaction terms

As mentioned before, the crash severity is specified to be one of four discrete categories. With these levels, we perform multinomial logit (MNL) regression model to analyze the factors contributing to crash severity, which is the most common technique used to identify the relation between the dependent and independent variables.

The response variable is the injury severity of the crash, represented by the following four categories: fatal (level 1), severe injury (level 2), visible injury (level 3), and complaint of injury (level 4). The crash location information, roadway, environment, and vehicles', drivers' and VRU' characteristics are included in the model as independent variables.

The MNL, as a form of generalized linear model, nominates one of the response categories of the response variable as a reference level, and calculates log-odds for all other categories relative to the reference level. Complaint of injury was selected as the reference level in the model of this paper. In the MNL model, we assume that the log-odds of each response follow a linear model, which is shown in Equation (1):

$$\eta_{ij} = log\ log\ \frac{\pi_{ij}}{\pi_{iJ}} = \alpha_j + x_i'\beta_j \tag{1}$$

where π_{ij}/π_{iJ} is the odds ratio (OR) that an observation i falls in category j as opposed to the reference level J, α_j is a constant term, and β_j is a vector of regression coefficients, for $j = 1,2,\ldots,J-1$. The probabilities of the MNL model can be written as

$$p_{ij} = \frac{exp\ (\eta_{ij})}{\sum_{k=1}^{J} exp\ (\eta_{ik})} \tag{2}$$

Note that Equation (2) will automatically yield probabilities that add up to one for each observation. Also, the variables will be selected based on the result of the adjusted pseudo R-squared of the MNL model.

In addition, analyzing the interaction terms of the MNL model helps to find critical crash scenarios that have a higher crash risk to VRU. The scenarios may have different crash characteristics in relation to the VRU, vehicle and environment, which may result from different underlying factors. We can expect that the coefficients of some variables are significant in some scenarios, but not necessarily significant in other scenarios. Therefore, we perform MNL regression models on the movements preceding collision and the corresponding interaction terms, which are considered movement combinations for VRU and vehicles.

Having the estimation of interaction effects available, the MNL models could provide the estimated coefficients for the combinations of some independent variables, for example the movements of VRU and vehicle preceding the collision. In such cases, the coefficients represent the log of OR of the collision severity for a specific combination of movements. Considering the crash data, we will assess drivers' behaviors to build the basis for the simulation efforts. Behaviors include, but are not limited to, running a stop sign/red light, or sudden lane-change. We will also use the historic crash data to characterize intersection design characteristics that where different accidents happen. Finally, we will develop several key scenarios for the simulation combining intersection design, behaviors, crash odds, technology characteristics, weather, and other system conditions. These scenarios will be implemented in a simulation platform to examine which IVT will be most efficient in a specific scenario.

Case study and data description

Lubricating the ultimate step of microscopic simulation for this project, the California historical crash data, collected from cities' traffic safety statistics, help understanding the underlying factors influencing the crash rates involving VRU. In preparation for the macroscopic traffic safety factor analysis based on a regression modeling method, which is described in the following section, it is naturally salient to select cities with high VRU safety concerns as "hotspots" for research.

The case study city selection incorporates the existing research results from the 2018 Office of Traffic Safety (OTS) Crash Rankings, which are based on the Empirical Bayesian Ranking Method. It adds weights to different crash statistical categories including observed crash counts, population and daily vehicle miles traveled (DVMT). In addition, the OTS crash rankings include different types of crash with larger percentages of total victims and areas of focus for the OTS grant program. In conjunction with the research context, two types of crash rankings are focused on, namely pedestrians and bicyclists. The OTS rankings also divide the cities into seven groups by population. Studied by Clark and Cushing (2004), population density of city is associated with number of VRU victims for the reason that higher population might contribute to higher exposure of VRU traffic and thus more crashes might happen.

Without selecting all the cities ranging from hundreds to millions of populations, selecting safety hotspots where high-frequency VRU-involved crashes take place each year facilitates the process of understanding VRU safety factors and thus creating meaningful and effective scenarios for traffic simulation. Therefore, cities selected as cases for study is taken on priority preceding the data collection and analysis.

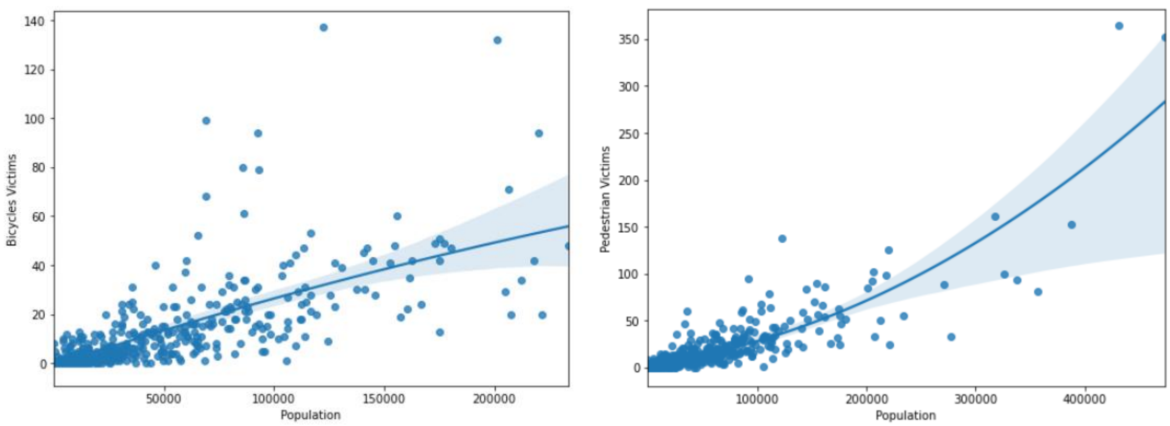


Figure 1. Relation between number of crash victims and population.

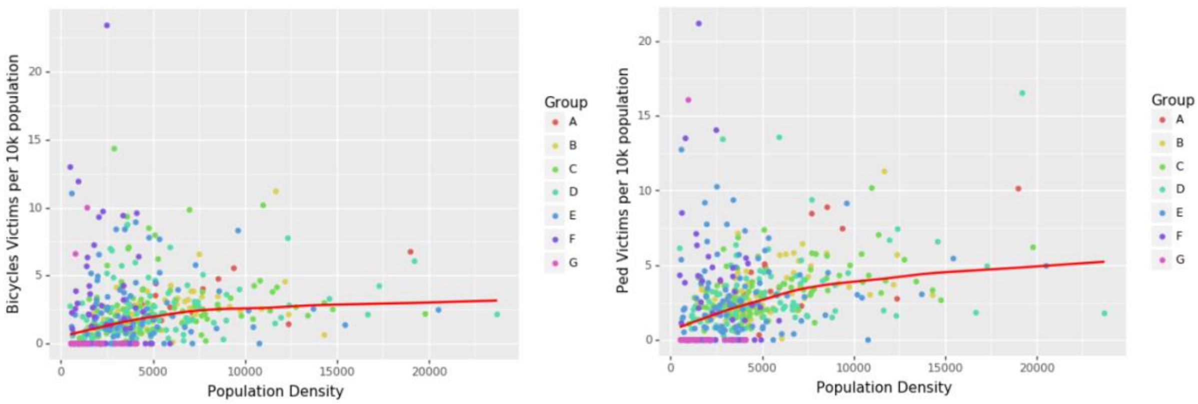


Figure 2. Relation between number of crash victims per 10k population and population density.

To quantitatively investigate the inference, we study the relation between population and number of crash victims. From Figure 1, we can see that the number of people and the number of crash victims is not typically linear, but the number of crash victims increases faster as the population increases. Moreover, we can see from Figure 2 that the positive correlation between the number of victims per 10k population and the population density gradually weakens or even does not exist as the population decreases starting group E. The inference can be validated by the two figures, concluding that cities in population groups from A to D are more of our research interest. So, we collect cities with top OTS pedestrian/bicyclist crash ranking from group A (populations over 250,000) to group D (populations 25,001-50,000), which are shown in Table 3. Hence, seven of the cities are selected as cases for study and their corresponding historical crash data will be collected and analyzed in the following section, namely San Francisco, Oakland, Berkeley, Santa Monica, Davis, West Hollywood and East Palo Alto.

Table 3. Top 3 cities with highest OTS crash rankings from different population groups.

Group	Ranking	Type of Crash	
		Bicyclist	**Pedestrian**
Group A – 15 cities, populations over 250,000	1	San Francisco	Oakland
	2	Long Beach	Long Beach
	3	Sacramento	San Francisco
Group B – 58 cities, population 100,001-250,000	1	Berkeley	Berkeley
	2	Huntington Beach	El Cajon
	3	El Monte	Pasadena
Group C – 106 cities, population 50,001-100,000	1	Davis	Santa Monica
	2	Palo Alto	Santa Cruz
	3	Santa Monica	Merced
Group D – 94 cities, population 25,001-50,000	1	East Palo Alto	West Hollywood
	2	Menlo Park	Eureka
	3	San Luis Obispo	Beverly Hills

The Safe Transportation Research and Education Center (SafeTREC)[1] at the University of California, Berkeley, develops the Transportation Injury Mapping System (TIMS)[2] to provide a quick, easy and free access to California crash data provided by the Statewide Integrated Traffic Records System (SWITRS). We collect five-year-long crash data with 23,832 observations in total, which are from 01/01/2014 to 12/31/2018, from the 20 cities selected as cases for study in the state of California. The crash data includes bicyclist and pedestrian collisions with vehicles resulting in injuries across four types of crash severity: fatal, severe injury, visible injury and complaint of injury. The data consists of three tables including collision dataset, involved "parties" dataset, and victims dataset. In particular, we use the "collision" and "parties" datasets that contain enough information for modeling. The rows in the crash data are built based on each case of a crash and includes information such as weather, road surface, road condition, control device and lighting. The "parties" dataset includes information specific to each vehicle or VRU such as age and sex. To perform a party-by-party analysis, we attach the datasets of each crash to every pair of VRU and vehicle that involved in a specific collision. The task has been accomplished using a python script. For example, Figure 3 shows the distribution of crashes in San Francisco

[1] https://safetrec.berkeley.edu/
[2] https://tims.berkeley.edu/about.php

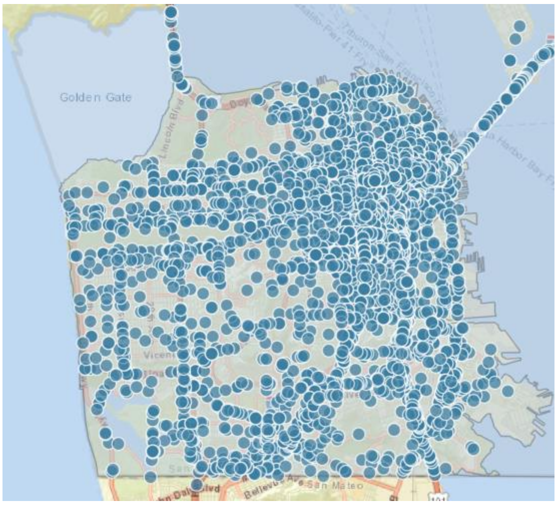


Figure 3. Distribution of crashes in San Francisco by TIMS.

The variables are selected based on the empirical results from existing literatures and records with missing data are dropped. After the data merging and cleaning process, 12,683 pedestrian-involved crash cases and 11,149 bicyclist-involved crash cases are selected and used in the following modeling. The crashes are all two-party collisions at signalized intersections involving vehicles and VRUs, which means that one party in a specific collision is driver and the other one is either bicyclist or pedestrian. Other types of crashes, such as single-vehicle collisions and multiple-party collisions are not considered in the study.

Microscopic Traffic Simulation

IVTs enhance safe driving by extending driver’s perception of incoming conflicts, especially at intersections where drivers deal with multiple movement at the same time. In this section, we evaluate the effectiveness of IVT on enhancing VRU’s safety at intersections. Specifically, our methodology can be split into four parts:

1) Define the microscopic factors in driving behavior that lead to crashes;
2) Summarize the literatures and categorize different types of IVT to study;
3) Implement the imperfect driving behaviors and IVT in micro-simulation; and
4) Conduct sensitivity analysis to estimate the IVT performance with different influence factors.

Limitations in perception of drivers and VRU

The existing intersection control systems in use, either two-way/four-way stop control or traffic signal control, are all designed to be collision-free, which simply assume that all the traffic participants can predict the incoming conflicts and follow the rules of system design. Except for the rare cases where traffic violations are committed deliberately, most accidents occur due to the limitations in the perception of drivers and VRU. Typically, the perception without driving assistance is purely vision-based. In this study, we specify the visual limitations in two aspects:

1) driver's and VRU's blind spot, defined with visual acuity; 2) driver's and VRU's random inattention.

Visual acuity

It is commonly acknowledged that vision-based perception of drivers or VRU are not all-rounded. Among the literatures modeling and testing for the field of view, we summarize the three key parameters to describe the perceptual limits. Objects beyond the limit is regarded as invisible in this study. In the simulation tool, the visual acuity parameters can include two parts: 1) generic part: the VRU and drivers share the same basic visual acuity decided by the environmental factors (e.g., weather and light conditions); and 2) individual part: the basic visual acuity is adjusted by the individual characteristics such as age, vision, clothing (e.g., reflective clothing can be seen more clearly at night) and light using (high-beam or low-beam). The two parts of parameters can then provide different parameters of reaction for each of the individuals in simulation.

- Front-view distance, subject to lighting and weather. For instance, front-view distance under daylight and clear weather is 224 m, while that in foggy weather is less than 100 m. On streets with poor light conditions, the average view distance at night is 108 m when only low beams are used. Using high beams and pedestrians wearing bright clothes will increase the average view distance to 228 m, which is close to the view distance during the day. Conversely, when the low beam is used and there is a car in the opposite direction, the average view distance is only 82 m.
- Front-view angle, which decreases with driving speed. The reference values of view angle with corresponding speed value are listed in Table 4. For the speed values in between, the front-view angle value can be estimated by interpolation.

Rear-view angle, covered by the left and right rearview mirror. The areas within rearview mirror coverage on both sides are regarded as visible. The remaining areas between rear-view angle and 90° are randomly inspected. For instance, Kedowide et al. find that only 83.0% of the drivers perform blind spot checks in an experiment (Kedowide, Gouin-Vallerand, and Vallieres 2014).

Table 4. One-side ideal view angles at different driving speeds.

Speed (mph)	One-Side Reference View Angle (degree)
18	60
50	30
60	22.5
80	15

The fields of vision and blind spots applied in this study are illustrated in Figure 4 and Figure 5, where parameters are listed. The space around the vehicle is split into three types. The 100%

visible areas are remarked in blue; the randomly visible areas are remarked in red; the rest are considered as 100% invisible. We also differentiate the blind spots definition between passenger car and truck. Comparing Figure 4 and Figure 5, we see two major differences of trucks from passenger cars:

- Blind spot in the front. Because of the high sitting position of truck driver, the objects that are very close to the truck in the front may not be observed directly. For passenger car, there is no blind spot in front.
- Differentiated left and right rear-view angle. The passenger car has equal rear-view angles left and right 21.8°. The left rear-view mirror is deliberately enhanced for truck, which expend the left rear-view angle to 75.2°.

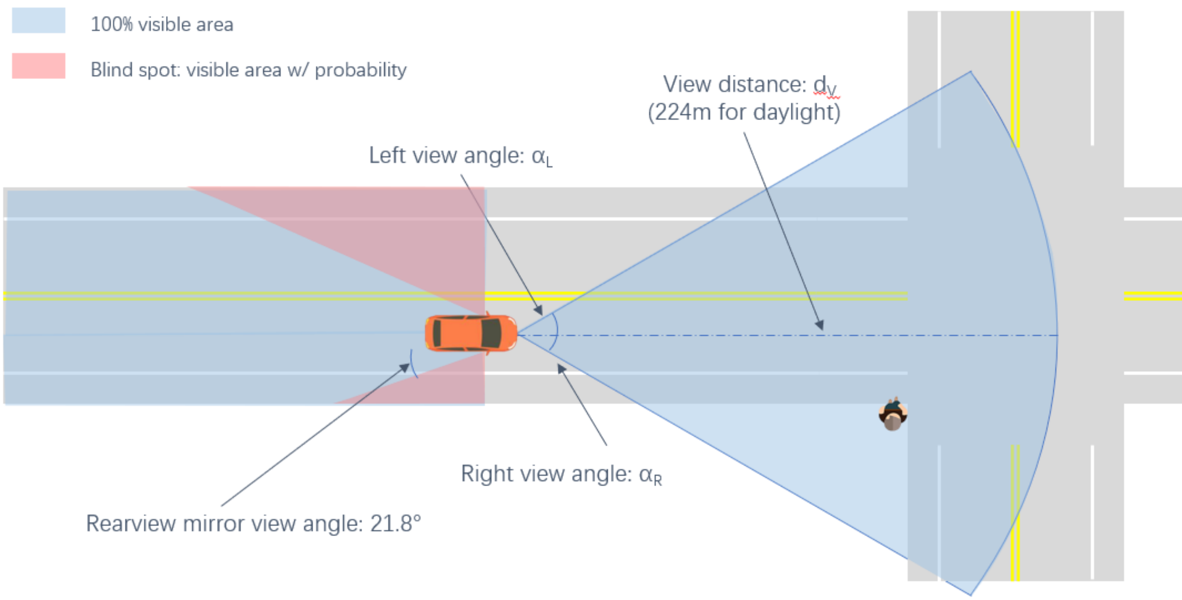


Figure 4. Peripheral vision in visual acuity when driving without IVT (passenger car)

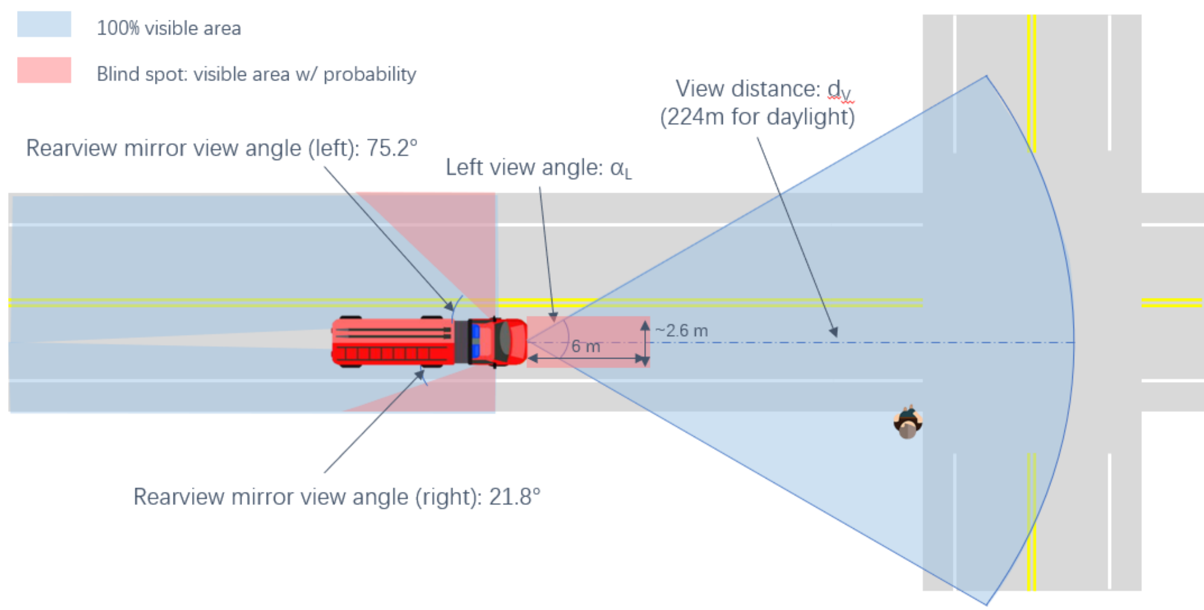


Figure 5. Peripheral vision in visual acuity when driving without IVT (truck)

Moreover, we also specify the visual acuity of VRU. Due to the low progress speed of VRU, the speed dependent front-view angle is not relevant. Based on the results from a natural study in (Hammoud 2008), we set the front-view distance to 50m and the front-view angle to 120°. No rear-view angle is set up for VRU.

Driver's random inattention

Besides the blind spots that have been deterministically defined on the 2D plane, driver's random inattention is also a major source leading to crashes. This term describes the generalized imperfect driving behavior without specific causal factors. In the driving process, drivers may be distracted from time to time such that they don't react to the conflicting objects at all. In macro-level analysis, this behavior is usually represented as greater reaction time. However, the micro-simulation deploys constant time step which implies that the decision update gap is unchangeable within the simulation run. Therefore, we set up a probability value in simulation which allows passenger car or truck to be totally blind randomly in some simulation time steps. Such behavior can be mitigated with IVT warning messages.

Definition of IVT

Various IVT have been developed to actively compensate the human's limited perception. Although great efforts have been made on optimizing detection accuracy and communication latency, no study compare the technologies from the mechanism's aspect. In this study, we select four typical technologies for comparison, which covers almost all the current active safety technologies. Because we focus on the effectiveness with respect to system structure, it is reasonable to assume the communication infrastructure and software all work in optimal states.

Blind Spot Detection (BSD)

BSD is the typical sensor-based system equipped in vehicle, which directly targets the vehicle's blind spot. It is widely used to avoid collisions in vehicle's lane change process. As is shown in Figure 6 and Figure 7, the sensors construct a rectangle area in blue which overlaps the blind spot areas in red. Specially for truck in Figure 7, a BSD detection area covers the blind spot in the front. Any objects that appear in the BSD detection area will trigger the warning alarm., which can reduce the driver's reaction time by 34.3% on average (Chang et al. 2009). In other words, it can significantly mitigate driver's inattention if necessary. BSD doesn't require the VRU to have any devices equipped for protection. Its short detection distance, on the other hand, may show its effectiveness in crash avoidance with VRU only when the vehicle is in slow movement and conducting left/right turn.

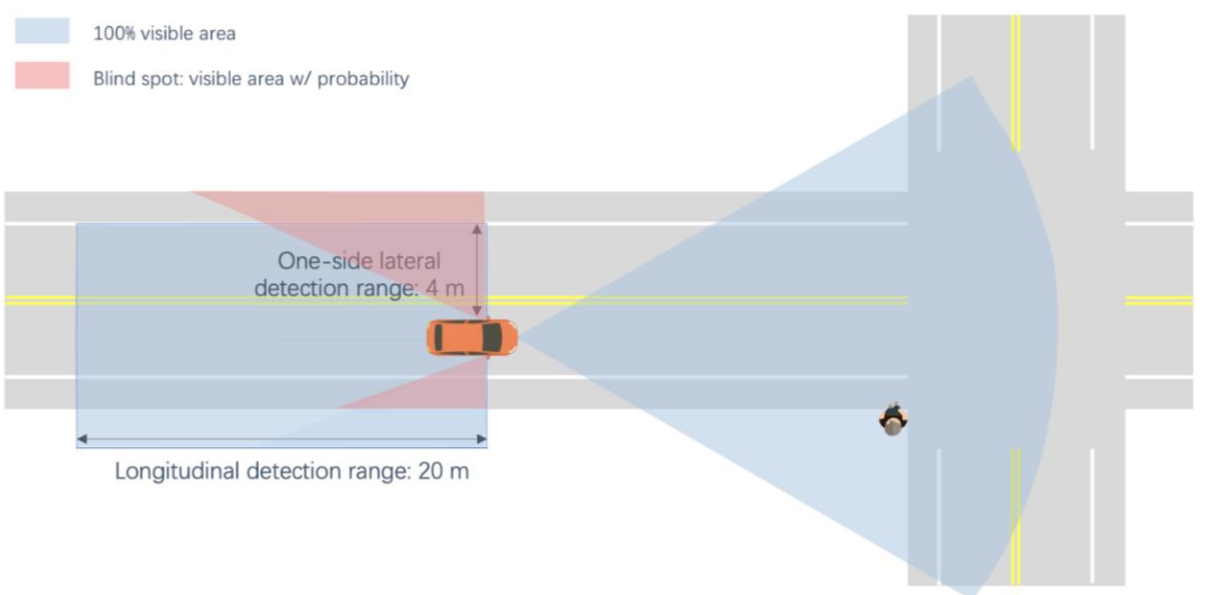


Figure 6. Blind spot detection area provided by BSD for a passenger car.

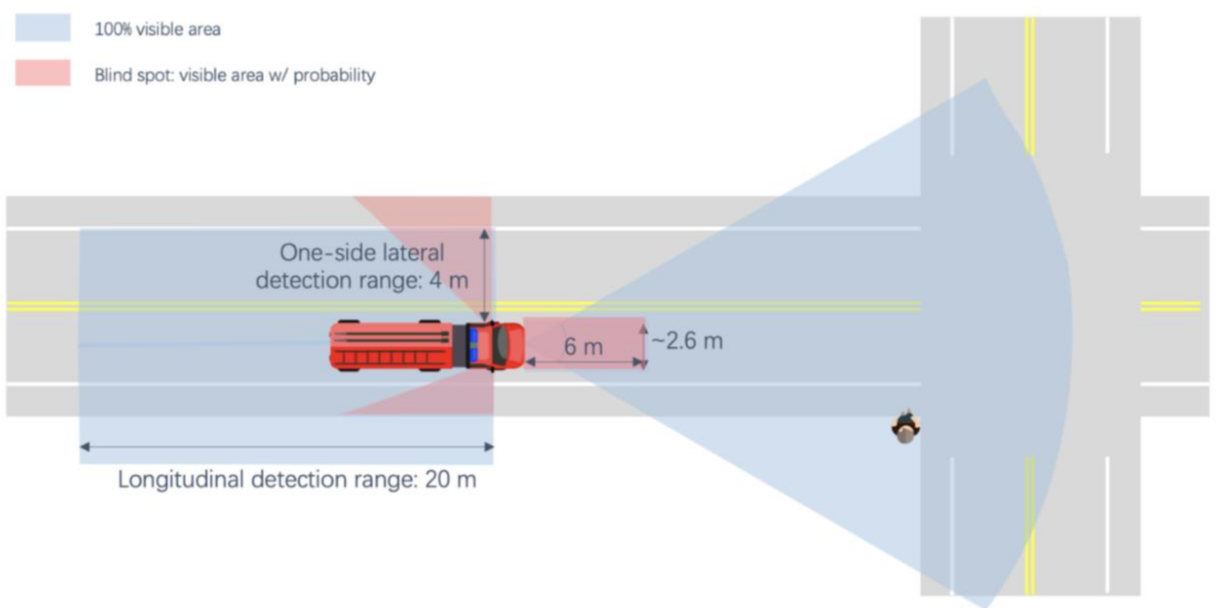


Figure 7. Blind spot detection area provided by BSD for a truck.

VRU Beacon System (VBS)

VBS is a one-way wireless-communication-based system. As shown in Figure 8, it requires the VRU to carry a device as message sender; and the vehicle to carry a receiver onboard. When a pedestrian or a bicycle approach the intersection, the device will beacon the location and heading to all the vehicles around. The vehicles who carry the receiver will then predict the VRU's trajectory and check if they have risk to crash. If so, a warning alarm is to be triggered such that the driver can slow down in advance.

In this system, VRU is always a sender; and vehicle is always a receiver, which grant VRU with higher priority but cannot alarm even if a VRU violates the intersection control rules. It can undermine the highway capacity and put vehicles to the vulnerable position. On the other hand, VBS can use Bluetooth which supports the VRU to communicate with vehicles within 100 m. This range may be enough in urban areas with typical vehicle speeds up to 35mph. Also, since the Bluetooth has been widely used in smartphone, this technology can be utilized to protect the disabled at the intersection.

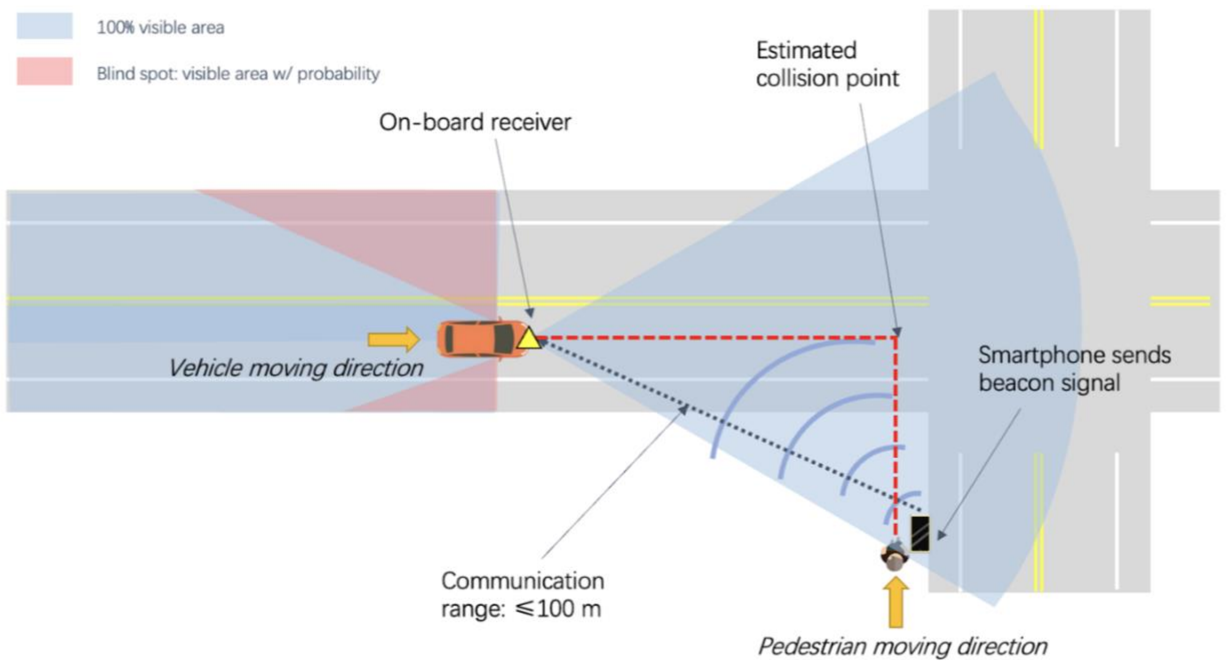


Figure 8. Illustration of VBS system.

Bicycle/Pedestrian to Vehicle Communication (BPTV)

BPTV is a two-way wireless-communication-based system. In addition to the VRU-to-vehicle communication process that has been covered in VBS, BPTV enables vehicle to send message to VRU. This requires both vehicle and VRU to be sender and receiver at the same time (see Figure 9). The two-way communication also makes possible of alarming VRU to stop in advance.

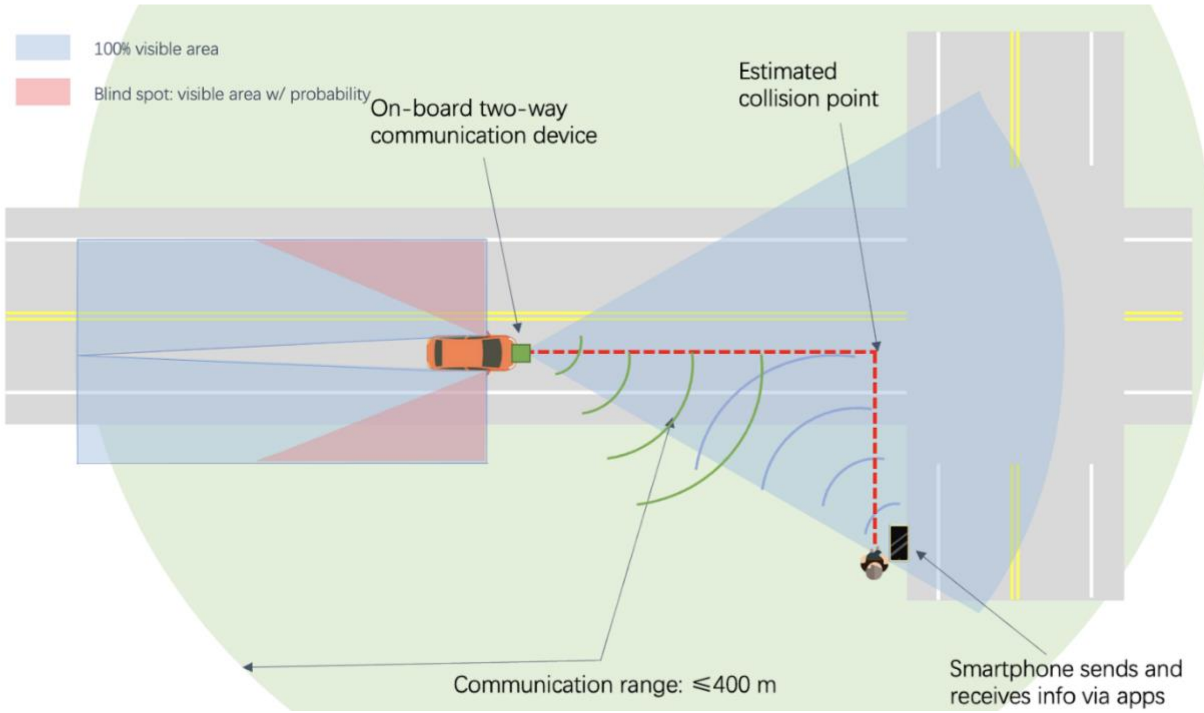


Figure 9. Illustration of BPTV system.

Although introducing 5G to BPTV system can expand communication range to 400 m, the recognition accuracy hindered by prediction algorithms may not get improved. For example, Lidar has a recognition rate of 97.1% for vehicles within a range of 25-40m (Zhao et al. 2019), and a recognition rate of 79.3% for pedestrians within a range of 50m (K. Liu, Wang, and Wang 2019). In that case, predicting a conflict beyond 100m may not facilitate safe driving.

Intersection Safety (INS)

Both VBS and BPTV are decentralized V2V systems, where vehicles and VRU communicate directly. In this context, unless all the vehicles and VRU are equipped with wireless communication devices, there is no guarantee that following the warning message can be safe, since there are always some objects that cannot be detected by the system. As a centralized V2I system shown in Figure 10, INS needs to collect the real-time data of all the vehicles and VRU around the intersection. Thus, the safety guidance provided by INS performs more consistent and reliable.

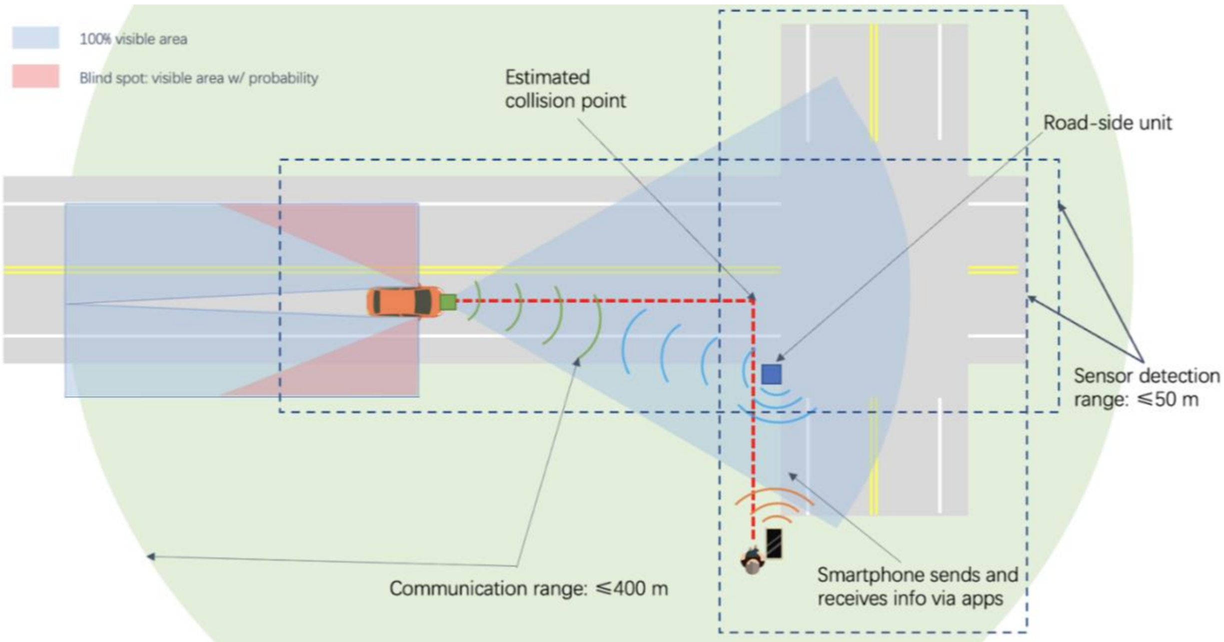


Figure 10. Illustration of INS system.

On the other hand, it is expected that building up and running the INS system is super costly. To realize the full coverage of traffic objects detection and recognition, the INS system must integrate multiple surveillance technologies, e.g., wireless probes, sensors, and cameras. This will impose high cost to the system construction. Meanwhile, the centralized communication pattern makes INS system highly responsible for incidents. Any incidents occurring will be imputed to the failure of INS system.

Summary

The major characters of the four IVT are listed in Table 5. In general, BSD is the most mature technology to diminish blind spot areas, while its benefit to VRU safety is also limited compared with the other three IVTs that have inter-device communication. VBS is a viable approach to help VRU at the cost of traffic throughput reduction. In contrast, BPTV and INS exhibit the most promising performance. BPTV can suffer from stability issues when the market penetration is low, while INS has the highest construction and operational costs.

Table 5. Summary of technical differences across the four IVT.

Features	IVT			
	BSD	VBS	BPTV	INS
Communication approach	Vision / Sensor	Wireless one-way	Wireless two-way	Vision/Wireless/Sensor
Require trajectory prediction algorithm	No	Yes	Yes	Yes
VRU-equipped device	None	Sender	Sender & Receiver	Receiver (Sender is optional)
Vehicle-equipped device	Sensor	Receiver	Sender & Receiver	Receiver (Sender is optional)
Vehicle's warning message triggered	VRU in BSD detection range	• Vehicle receives beacon signal from VRU • VRU's trajectory be predicted to conflict with vehicle • Emergency brake required for vehicle to avoid collision	• Vehicle receives beacon signal from VRU • VRU's trajectory be predicted to conflict with vehicle • Emergency brake required for vehicle to avoid collision	• Vehicle receives beacon signal from VRU • VRU's trajectory be predicted to conflict with vehicle • Emergency brake required for vehicle to avoid collision
VRU's warning message triggered	NA	NA	• VRU receive beacon signal from vehicle • Vehicle's trajectory be predicted to conflict with VRU • VRU's gap to collision is small enough	• VRU receive beacon signal from vehicle • Vehicle's trajectory be predicted to conflict with VRU • VRU's gap to collision is small enough

Implementation in SUMO

We implement the simulation scenarios above in SUMO, an open-source, highly portable, microscopic, and continuous traffic simulation package designed to handle large road networks. A basic SUMO model consists of a variety of objects, including:

- ***Network components*** (e.g., edge, lane, junction), which define the spatial topology and connectivity of highway infrastructure. These objects are static in the simulation run.
- ***Traffic participants*** (e.g., vehicle, bike, person), which encapsulate the real-time state variables of moving objects in the simulation run (e.g., position, speed). In each simulation time step, these state variables are updated.

The driving behavior models, which describe the interactive movements of traffic participants, are implemented in SUMO to prevent collisions, including:

- ***Car-following models***, which regulate the rear-end interactions between leader and follower.
- ***Lane-changing models***, which regulate the lateral movement of vehicles.
- ***Junction-control models***, which define the strategies of scheduling passage of traffic participants at intersections.

The existing junction-control models are collision-free under the assumption of perfect knowledge, which means each object in simulation can perceive all the incoming foes. To represent the driver's sporadic inability of identifying conflicts and IVT compensation effects, we insert the filtering logic into the current junction-control model in SUMO source code (see Figure 11). The resultant collisions are output using the SSM module for comparison.

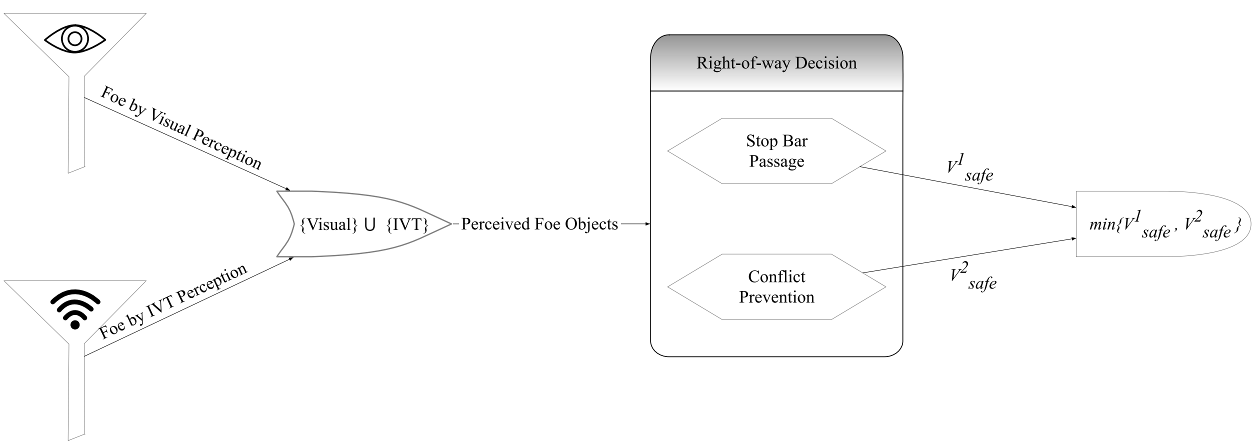


Figure 11. Logic flow charts of junction control and filtering modification.

Logic process of SUMO junction-control model

The junction-control model is the module that arranges the interactions between vehicles and VRU. In each simulation step, it is preceded by each traffic object that is approaching the junction and returning 1) whether the ego vehicle or VRU should pass or brake; and 2) What maximum speed is safe to follow the junction control rule and prevent collision. To apply the right-of-way decision to all the approaching vehicles and VRU in the many-to-many lane context, SUMO introduces a structure of right-of-way (ROW) matrix, as shown in Figure 12. Detailed control logic about the SUMO junction-control model that governs vehicle dynamics are introduced in this document (Krajzewicz and Erdmann 2013).

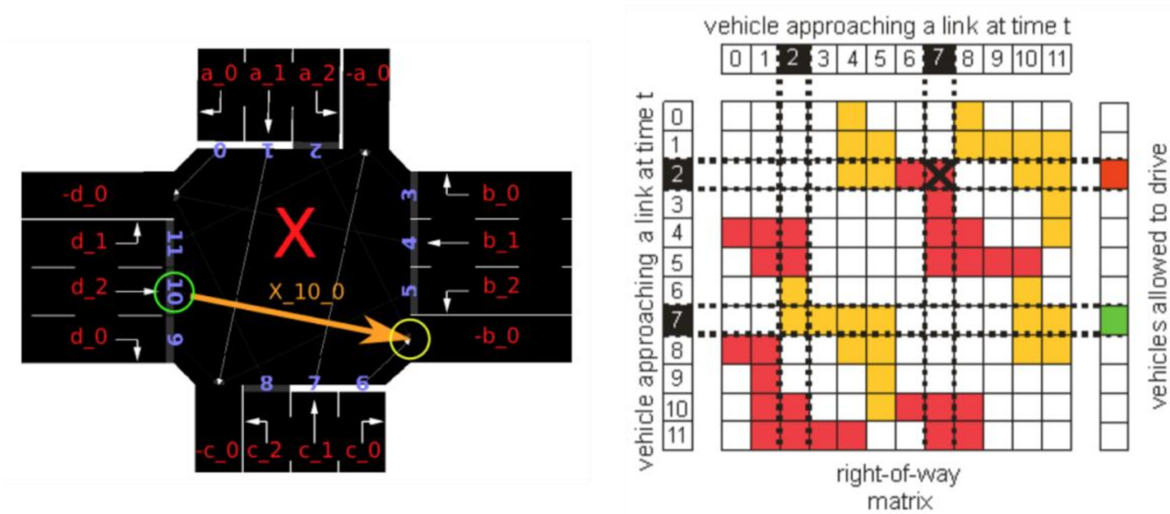


Figure 12. Passage decision making using a right-of-way matrix (Krajzewicz and Erdmann 2013).

The decision process is executed between one "ego" object and one "foe" object. Based on the different states of "ego" and "foe", we split the right-of-way decision process into two types.

1) Stop bar passage decision. This process is implemented to "ego" objects that have not yet entered the junction and all the "foe" objects who will pass the junction in the future simulation steps. If a potential collision is detected or the stop bar is in red traffic light, then the "ego" object will stop before the stop bar and calculate accordingly the safe speed, denoted as v_{safe}^{1}. Otherwise, with no conflict perceived, the "ego" object will select the safe speed as the lane speed limit. This process can also be interpreted as scheduling the time window for each vehicle, which is the core of junction-control logic.
2) Conflict prevention decision. This process is implemented to every one of "ego" objects, either in the normal lane or inside the junction, and the "foe" objects inside the junction. Because the objects that have already entered the junction always have higher priority to the object outside the junction for passage, the "ego" objects that have not entered will have no choice but brake, with safe speed v_{safe}^{2} calculated. For the "ego" objects that are also inside the junction, a similar ROW matrix is calculated, which assigns the right of way to the object passing the conflict point earlier. This process enables the emergency braking to happen, which is usually the case when IVT take effect.

After the two logic processes, the final safe speed is determined by taking the minimum value of v_{safe}^{1} and v_{safe}^{2}.

Filter implementation

We design and implement two filters to realize the junction-control with imperfect knowledge. The filters are inserted before the right-of-way decision process above. When the filters take effect, the “foe” object will be ignored by “ego” object.

1) Visual perception filter. This filter is designed for modeling the driver’s perception limit, especially in the scenarios without IVT equipment. From this filter, the “foe” object is excluded from the right-of-way decision process either when it is in the blind spot of “ego” object or when the “ego” is distracted.
2) IVT perception filter. As a compensation of driver’s visual inability, the filter may exclude fewer objects, which allows the “foe” objects visually excluded to be covered and triggered by IVT. This filter is designed specifically based on the characters of IVT. For instance, the BSD technology has no prediction process and will trigger the warning immediately after some objects are covered in the camera range. We assume these “foe” objects become visible to the driver. In contrast, the other advanced technologies including VBS, BPTV and INS will trigger the warnings only if the “foe” object is detected, predicted to have collision, and urgent enough to meet with the alarm trigger thresholds.

The two filters are run parallelly and return the set of visible “foe” objects separately, which are joint as the whole set to input to the right-of-way decision process.

Uncertainty Parameters in SUMO

Besides the deterministic factors that cause safety issues, we further explore the random factors in our simulation-based assessment. In the visual perception filter, we utilize a junction-control model parameter “ignore foe probability” to address the driver’s random distraction behavior as an additive to the blind spot definition. Moreover, we introduce three parameters into the VBS/BPTV/INS scenarios in the IVT perception filter: 1) wireless communication error; 2) collision prediction error; 3) alarm triggering thresholds. Following a variety of literature, the values of these parameters are selected as illustrated below.

The relation between ignore probability and driver’s inattention

When the driver is driving without IVT assistance, he may be distracted or not paying attention, which can be internalized as Ignore Foe Probability in SUMO. Kedowide, Gouin-Vallerand, and Vallieres (2014) conducted a field test on 60 test participants to characterize driver brake perception-reaction times at the onset of an amber phase actuation at a high-speed signalized intersection approach. Results show that the percentage of participants with reaction times more than 1.0 sec, which is the TTC threshold of a critical collision event, is approximately 94% (Kedowide, Gouin-Vallerand, and Vallieres 2014). It means that 94% of drivers can react properly to the critical event when a VRU is perceived. Therefore, we consider setting the ignore foe probability in SUMO to 0.06 in the context of driving without IVT.

VBS/BPTV/INS communication accuracy

In technologies involving communication between vehicles and VRU, the success rate of communication transmissions can also be internalized, which is regarded as communication error (CE) in this project. For example, packet delivery rate (PDR) can be considered as an evaluation index for CE of VBS/BPTV system using dedicated short-range communication (DSRC). Kedowide et al., (2014) also conducted an experiment to compare the PDR performances of DSRC and LTE technologies. As Figure 13, the previous results suggest that the PDR for DSCR at LOS condition can be as high as 92.4% at the distance of 50 m, 90.3% at 150 m and only 70.3% at 400 m. In SUMO simulation, we incorporate the results and internalize them as communication errors that are based on the distance between the vehicle and the VRU. The distance-based communication error is also adapted to a curve based on the research of Kedowide et al. (2014).

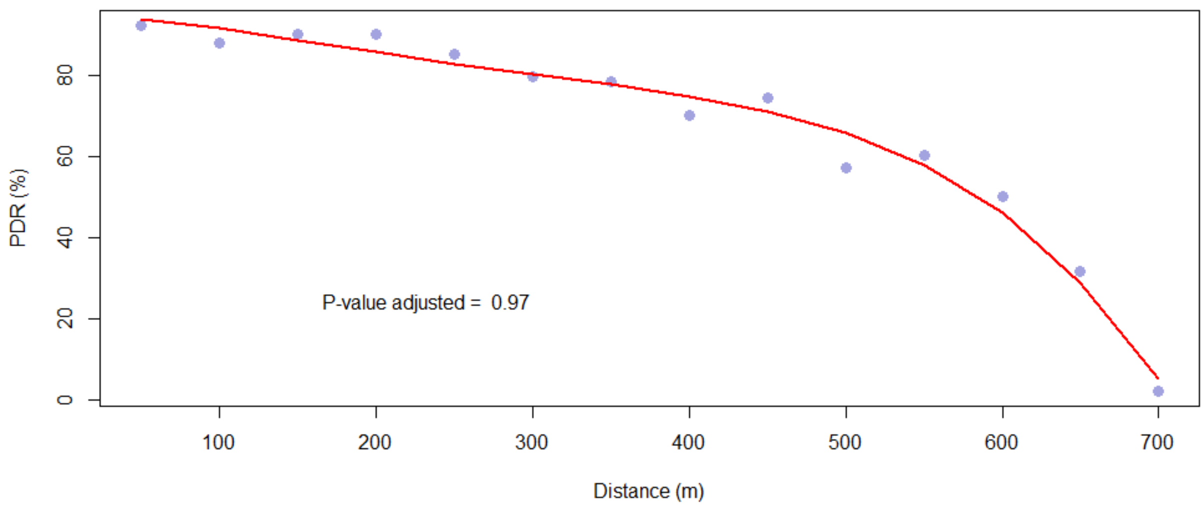


Figure 13. Relation between packet delivery rate (PDR) and communication distance.

The implementation of BPTV communication efficacy can be divided into two parts: i) PDR in order to evaluate the effectiveness of DSRC communication on the vehicle side; and ii) DSRC communication effectiveness of DSRC on the VRU side. The two sides can be viewed as two independent probabilities when being applied in the simulation. In terms of VRU and vehicle communication, the parameters required by INS are consistent with BPTV.

When the CE parameter is applied to VBS and BPTV, the difference lies in the object of the parameter. In the VBS scenario, the VRU acts as the signal transmitter, and the vehicle-mounted equipment or the smartphone of the driver acts as the signal receiver, and the only object of CE is the vehicle. However, in the scenario of BPTV, there is a two-way communication, which means that the vehicle works as a signal receiver as well as a sender, and vice versa for the VRU. However, the two-way communication occurs at the same time and consist of two independent events of communications. Therefore, the CE parameter can utilize the same distance-based curve as VBS when BPTV is active in the simulation scenarios.

BSD/VBS/BPTV/INS VRU conflict prediction accuracy

The mechanisms of VRU prediction are different for BSD and the latter three technologies. Existing BSD mostly relies on the recognition work of camera and/or radar, so prediction error can be externalized as the recognition accuracy of the BSD system for objects that exist in the blind zone. Hammoud (2008) suggests that the radar-based BSD system can reach accuracies of 98.38% and 98.34% under daytime and nighttime conditions, respectively. Also, Djamel et al. (2020) suggest that vision-based BSD systems have the detection accuracy of 91.11% with a 41-vehicle sample. Therefore, we consider setting the VRU prediction error in SUMO to 0.09 under the BSD scenario.

Apart from the communication successful rate with respect to the three IVT, their detection accuracies on VRU are also important parts when internalizing the VRU path prediction error. In actual scenarios, VBS, BPTV and INS all require VRU or vehicle movement data (e.g., GPS data) from specific devices or smartphones such as location, speed, direction of movement, for short-term trajectory prediction, which is based on successful communication. By predicting the short-term trajectory, the IVT system can detect potential conflicts and thus issue a warning to driver and/or VRU.

Various machine learning methods are used to utilize the short-term paths of both vehicles and VRU to predict whether a potential collision point exists. Chang et al. (2009) propose a predictive method using mobile phone to collect GPS data from 14 participants. The prediction part was made by a decision tree created from the movement patterns. The results show that the approach achieved 80% accuracy in destination prediction and only 60% in 1-step prediction. K. Liu, Wang, and Wang (2019) present a method to predict pedestrian's next move by applying a mixed Markov–Chain Model (MMM) and by comparing the results against a Hidden Markon Model (HMM) and a Markov Model. The authors used 10 datasets generated by a simulator creating data from 1,337 pedestrians. The prediction rates reach up to 73.5%. Krajzewicz and Erdmann (2013) developed two neural networks for this work, leveraging information such as GPS, heading, and velocity. The results showed that the dead reckoning method makes 98% accurate predictions when the prediction time is less than 0.5 s but makes large prediction errors when the prediction time is more than 0.5 s. Therefore, we assume in the project that the prediction error of VRU path increases as the prediction time increases. We assume that within 0.5s of prediction time, the prediction accuracy of VRU path can reach 95%. Outside of 0.5s, the prediction accuracy decreases with the increase of time.

As for INS, since it has a second perception mechanism, which is sensor detection, we can expect INS to have a higher recognition accuracy rate than BPTV. According to Rothenbücher et al. (2016), the Lidar/camera sensor achieves on average 99.16% detection accuracy for pedestrian detection.

Safety warning message/alarm triggering

The safety warning messages, or alarms to vehicles help drivers reduce their reaction times to step on brake earlier to avoid potential collisions with VRU, and therefore the safety of VRU at intersections can be improved. This feature serves as important components in VBS/BPTV/INS technologies, except for BSD. The methods of warning triggering vary in previous research. Chang et al. (2009) propose a collision warning predicted framework that provides connected automated vehicle and alert driver when time to collision (TTC) is within specified thresholds. Besides, among the most popular safe stopping distance-based indicators such as TTC and PET, Deceleration Rate to Avoid Collision (DRAC) is also an effective indicator, which simplifies the process of calculating critical TTC/PET thresholds, directly indicates potential collision in SUMO and thus escalates the speed of SUMO simulation. It is defined as the minimum rate at which a vehicle must decelerate to avoid a possible traffic conflict. In the context of this study, potential conflict scenarios are considered when the DRAC exceeds a threshold braking value of 70% of the maximum braking deceleration rates for different types of vehicles and VRU.

Figure 14 shows the illustration of the simulation parameter structure, which is applied to modify the default ROW junction model, making traffic collisions possible in SUMO simulations.

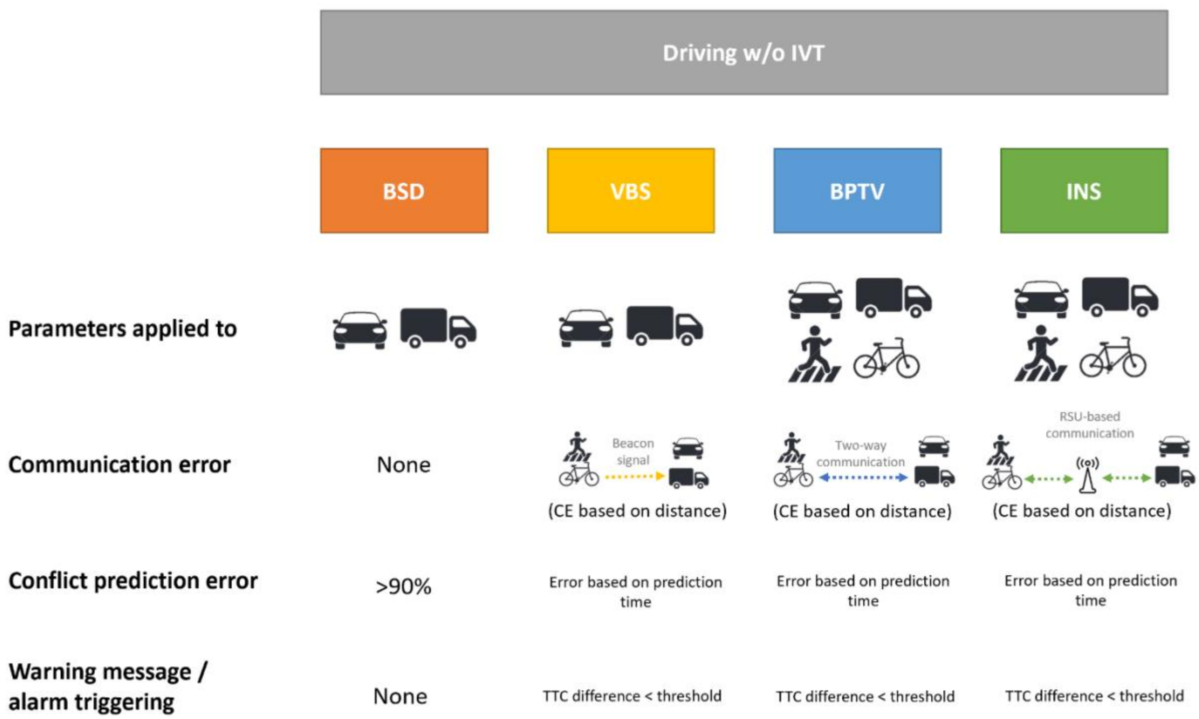


Figure 14. The simulation parameter structure in the modified ROW junction model.

Results and Discussion

Macroscopic: Crash Severity Modeling Results

A series of human/behavioral and environmental factors, which are commonly considered to have an impact on the crash severity, were analyzed using MNL models. All the independent variables from the crash data were input with category exclusion done based on the sample selection criteria. However, based on the original results, the p-values of some of the variables are larger than 0.1, which means that these variables are found to be insignificant and hence are removed from the list of significant variables.

Table 6 shows the results of the MNL models for both pedestrian- and bicyclist-involved crashes. All the estimated coefficients, which are log of odds ratios (OR) for the selected variables represent the effect of the variables on the specific fatal/injury level compared with the complaint of injury level. In addition to the coefficients of the selected variables in the MNL models, we estimate the coefficients of the interaction terms of different movements preceding collision. In general, these influencing factors can be divided into five categories: weather, road type, lighting, vehicle type and human characteristics, which are summarized as follows.

Table 6. Results of MNL regression models.

Diagnostics of MNL Models		
	Pedestrian Model	**Bicyclist Model**
Number of Observations	12,683	11,149
Residual Deviance	9813.299	7742.598
AIC	10047.3	7958.598

Independent Variables		**Dependent Variable:** Collision Severity Ref. level: Injury (Complaint of Pain)					
		Pedestrian Model			**Bicyclist Model**		
		Coef. & t-value			*Coef. & t-value*		
		Injury (Other Visible)	Injury (Severe)	Fatal	Injury (Other Visible)	Injury (Severe)	Fatal
Constant		-0.619***	-1.814***	-3.258***	-0.386*	-2.108***	-2.288**
		(0.17)	(0.27)	(0.51)	(0.22)	(0.41)	(0.93)
Weather Ref.: (A) Clear	(B) Cloudy	-0.104	-0.226	0.226	-0.076	0.138	-0.501
		(0.09)	(0.16)	(0.26)	(0.10)	(0.18)	(0.75)
	(C) Rainy	-0.469***	-0.443***	-0.285	-0.062	-0.251	0.582
		(0.12)	(0.17)	(0.31)	(0.19)	(0.41)	(1.06)
State Highway Indicator Ref.: (N) No	(Y) Yes	0.367***	0.506***	1.377***	0.194*	0.082	-0.465
		(0.12)	(0.17)	(0.25)	(0.12)	(0.24)	(1.03)
Lighting Ref.: (A) Daytime	(B) Dusk - Dawn	-0.203	0.059	0.329	-0.401***	-0.343	0.949
		(0.14)	(0.22)	(0.42)	(0.13)	(0.30)	(0.65)
	(C) Dark - Street Lights	-0.076	0.575***	1.057***	-0.208***	0.237*	-0.22
		(0.06)	(0.09)	(0.18)	(0.07)	(0.13)	(0.48)
	(D) Dark - No Street Lights	-0.015	0.951***	1.012*	-0.391	-0.068	-7.828
		(0.24)	(0.28)	(0.56)	(0.32)	(0.63)	(104.33)
	(E) Dark - Street Lights Not Functioning	0.583	1.046	1.319	-	-	-
		(0.62)	(0.76)	(1.15)	-	-	-
Truck Accident Ref.: (N) No	(Y) Yes	0.145	0.18	1.642***	0.379	1.051***	2.232***
		(0.28)	(0.41)	(0.45)	(0.26)	(0.40)	(0.81)

Independent Variables		Dependent Variable: Collision Severity Ref. level: Injury (Complaint of Pain)					
		Pedestrian Model			**Bicyclist Model**		
		Coef. & t-value			*Coef. & t-value*		
		Injury (Other Visible)	Injury (Severe)	Fatal	Injury (Other Visible)	Injury (Severe)	Fatal
PCF Violation Category Ref.: (00) Unknown	(01) Driving or Bicycling Under the Influence of Alcohol or Drug	0.344	2.016***	2.529***	1.449***	2.371***	2.356*
		(0.42)	(0.47)	(0.85)	(0.53)	(0.70)	(1.43)
	(03) Unsafe Speed	-0.1	0.632*	1.25	0.217	0.29	-0.541
		(0.25)	(0.38)	(0.77)	(0.19)	(0.41)	(1.11)
	(04) Following Too Closely	-	-	-	-0.245	-0.979	-9.636***
		-	-	-	(0.33)	(1.08)	(0.01)
	(05) Wrong Side of Road	0.638	1.549**	2.402*	-0.540***	-0.246	-0.928
		(0.56)	(0.71)	(1.28)	(0.17)	(0.37)	(0.93)
	(06) Improper Passing	0.138	0.796	-8.855***	-0.023	-0.409	13.168***
		(0.38)	(0.56)	(0.00)	(0.23)	(0.58)	(0.00)
	(07) Unsafe Lane Change	-	-	-	0.126	0.189	12.748***
		-	-	-	(0.24)	(0.53)	(0.00)
	(08) Improper Turning	-0.114	-0.179	-0.666	0.054	0.133	-2.174*
		(0.25)	(0.44)	(1.20)	(0.17)	(0.37)	(1.31)
	(09) Automobile Right of Way	0.043	-0.306	0.805	-0.027	0.272	-1.797
		(0.27)	(0.50)	(0.80)	(0.16)	(0.36)	(1.11)
	(10) Pedestrian Right of Way	-0.096	-0.039	0.201	-0.29	-0.229	-9.445***
		(0.20)	(0.33)	(0.67)	(0.27)	(0.69)	(0.01)
	(11) Pedestrian Violation	-0.023	0.298	0.208	0.016	0.351	0.645
		(0.21)	(0.33)	(0.64)	(0.30)	(0.64)	(1.35)
	(12) Traffic Signals and Signs	-0.244	-0.225	0.622	-0.148	0.824**	0.318
		(0.25)	(0.44)	(0.85)	(0.17)	(0.35)	(0.85)
	(14) Lights	-	-	-	-0.066	0.012	-8.149
		-	-	-	(0.41)	(0.84)	(106.04)
	(17) Other Hazardous Violation	-0.41	-0.109	10.194***	0.16	0.296	-1.408
		(0.35)	(0.57)	(0.00)	(0.18)	(0.40)	(1.32)
	(18) Other than Driver (or Pedestrian)	1.095**	1.158*	1.899**	0.297	-0.158	-8.158
		(0.44)	(0.64)	(0.90)	(0.40)	(1.07)	(112.21)
	(21) Unsafe Starting or Backing	-0.103	-0.397	-0.997	-0.209	-0.335	10.777***

Independent Variables		Dependent Variable: Collision Severity Ref. level: Injury (Complaint of Pain)					
		Pedestrian Model			**Bicyclist Model**		
		Coef. & t-value			*Coef. & t-value*		
		Injury (Other Visible)	Injury (Severe)	Fatal	Injury (Other Visible)	Injury (Severe)	Fatal
		(0.24)	(0.43)	(1.19)	(0.27)	(0.69)	(0.00)
	(22) Pedestrian or "Other" Under the Influence of Alcohol or Drug	0.247	0.299	-8.648	-0.348	-0.483	-8.958***
		(0.38)	(0.62)	(107.80)	(0.43)	(1.09)	(0.01)
VRU At Fault Ref.: (N) No	(Y) Yes	0.763***	0.775**	0.722	0.405***	0.319	0.688
		(0.22)	(0.35)	(0.65)	(0.16)	(0.31)	(0.85)
Driver At Fault Ref.: (N) No	(Y) Yes	0.282	0.069	-0.598	0.279*	-0.004	-0.204
		(0.20)	(0.33)	(0.65)	(0.16)	(0.32)	(0.95)
VRU Sex Ref.: (F) Female	(M) Male	0.300***	0.275***	0.420**	0.196***	0.184	0.368
		(0.05)	(0.08)	(0.17)	(0.06)	(0.13)	(0.50)
Driver Sex Ref.: (F) Female	(M) Male	-0.110**	0.159*	0.372**	-0.021	0.078	0.757*
		(0.06)	(0.09)	(0.19)	(0.05)	(0.11)	(0.42)
VRU Age Group Ref.: (A) Silent	(B) Baby Boomer	-0.413***	-0.725***	-1.076***	-0.058	-0.416	-1.807***
		(0.10)	(0.13)	(0.20)	(0.19)	(0.29)	(0.51)
	(C) Gen X	-0.495***	-0.776***	-2.041***	-0.228	-0.865***	-2.835***
		(0.10)	(0.14)	(0.26)	(0.18)	(0.30)	(0.61)
	(D) Millennials	-0.436***	-1.103***	-3.070***	-0.112	-0.824***	-2.837***
		(0.10)	(0.14)	(0.32)	(0.18)	(0.29)	(0.53)
	(E) Gen Z	-0.172*	-1.286***	-3.221***	0.151	-1.133***	19.379***
		(0.10)	(0.16)	(0.44)	(0.18)	(0.31)	0.00
Driver Age Group Ref.: (A) Silent	(B) Baby Boomer	0.1	0.006	0.658**	0.094	0.05	-0.437
		(0.08)	(0.13)	(0.28)	(0.09)	(0.19)	(0.60)
	(C) Gen X	0.09	0.024	0.244	0.229***	0.278	-0.107
		(0.08)	(0.14)	(0.31)	(0.09)	(0.19)	(0.59)
	(D) Millennials	0.158*	0.165	0.341	0.078	0.158	-0.288
		(0.08)	(0.13)	(0.30)	(0.09)	(0.19)	(0.58)
	(E) Gen Z	0.336***	0.536***	0.968**	0.309**	0.636***	-0.461
		(0.13)	(0.19)	(0.39)	(0.12)	(0.24)	(1.12)

*Note: *p<0.1; **p<0.05; ***p<0.01*

From the results, the impacting factors of VRU safety at intersections are discussed as follows.

Weather

In terms of pedestrian accidents, compared to clear weather, the OR of visible injury and severe collisions under rainy weather conditions decreases by 37.4% and 35.7%, respectively, compared to level 4 (no injury) pedestrian collisions. In terms of bicycle accidents, it is not found that the weather variable has significant estimated coefficients on the severity of crashes involving bicyclists. It is naturally assumed that rainy weather increases the severity of traffic accidents, but this may not be the case for collisions between vehicles and pedestrians at intersections, as negative but significant coefficients are found in the MNL model. However, it is clear that light conditions could affect pedestrian injury severity in good weather conditions (Table 6), but no evidence was found to associate pedestrian injury severity with adverse weather conditions (Table 6). The impact of weather changes on the severity of the accident can be multifaceted, which is reflected in vehicle speed, road surface, traffic volume and exposure, etc. Since weather is not found to significantly impact the injury severity of bicyclist accidents, we can hypothesize that the differences in bicyclist exposure in different weather conditions lead to statistically insignificant results. We can also assume that VRU traffic volume may have different distributions under different weather conditions. The exposure of bicycles in sunny weather could be higher.

State highway

The model results show that the OR for fatal and severe collisions is 4.0 and 1.7 times as high as that for level 4 collisions. Also, for level 3 visible injuries, the coefficients of the pedestrian model and the bicycle model are also significant, at 0.367 and 0.194, which means that their OR are 1.4 and 1.2 times, respectively. Compared to urban streets, state highways usually have lower bicycle and pedestrian traffic, but typically higher vehicle speeds of up to 65 mph or higher, whereas the speed limits for urban streets are often 35 to 40 mph. Therefore, for state highways, when a VRU crash occurs, it is much more likely to become severe, with VRU injuries.

Lighting

For pedestrian collisions, the model results show that the OR of fatal and severe crashes are 2.9 and 1.8 times respectively as high as that of level 4 crashes when the light condition is dark with streetlights. Moreover, the OR of fatal and severe crashes are 2.7 and 2.6 times, respectively, when it is dark with no streetlights. For bicyclist collisions, we also found that the OR of visible injury decreases by 18.6% while that of severe injury increases by 26.7%. We infer that lack of light at night is one of the factors leading to increased crash severity. Although streetlights are installed at some intersections, the visual acuity of drivers may not be high enough, resulting in a serious collision, reflected by the similar coefficients for streetlights and no streetlights in the dark.

Truck involved

The OR of fatal accidents for both pedestrian and bicyclist increase by 4.2 and 8.3 times more than those of level 4 accidents when a truck is involved in collisions, showing that trucks are an important factor in the increase in severity of VRU accidents, although these truck accidents account for less than 5% of the total sample of five years. This influence can be mainly analyzed for two aspects. For one thing, large trucks have larger blind spot areas than cars and SUVs at close range or when turning, and there is also a difference in inner wheels, which makes it difficult to perceive pedestrians and bicycles nearby. Also, even if truck drivers are aware of the dangers, trucks usually have a longer braking distance, making for a higher relative speed of the vehicle at the moment of collision, which increases the severity of the accident.

VRU and vehicle characteristics

The VRU and the driver's fault, gender, age and other personal characteristics all have different effects on the severity of the accident. If the VRU involved in the collision is at fault, the OR of severe and visible injury accidents for the pedestrian will increase by 117.3% and 114.5%, respectively, and this finding has the same effect on visible injury accidents for bicyclists, where the OR increases by 49.8%. Traffic violations placing one party at fault can cause serious crashes. In many cases, pedestrian violations, such as running a red light, can easily increase the severity of the accident if the pedestrian is not observed, or if the vehicle does not react in time (Table 4).

The model results also show that the OR in fatal/severe/visible injury pedestrian collisions involving male pedestrians are much higher than that of level 4, and the OR of a fatal bicycle collision involving male vehicle drivers is also higher than level 4. We can infer that male traffic agents may have over-optimistic decisions and aggressive actions in encountering potential conflicts, leading to an increase in collision severity. In addition, compared with the reference level, which is a silent age group, the OR of severe or fatal collisions in the other age groups for both pedestrian and bicycles drop by at least 70%, and the magnitude of the negative coefficients gradually increase as the average age of the group decreases. We can infer that age is an important factor affecting the severity of VRU accidents, and higher ages—65 and higher--will be more correlated to severe and fatal accidents for both pedestrians and bicyclists.

Through modeling and analyzing the influencing factors of the severity of VRU-related collisions, we can summarize the above environmental factors, characteristics of traffic agents, traffic volume and other factors that may increase the severity of the accident, to establish a typical scenario for subsequent traffic simulation processes.

Typical Crash Movement Combination

Table 7 provides the estimated coefficients for the combinations of these movements, where the coefficients represent the log of OR of the collision severity for a specific combination of movements. From the results of the two MNL regression models, we can summarize the factors associated to the severity of VRU-related collisions at intersections (explained in the aforementioned paragraphs) and can extract typical collision movement combinations through the coefficients of the interaction term. When considering the typical crash combinations, we assume that pedestrians can walk in both directions in pedestrian lanes, while bicycles are required to travel in the same direction as the flow of vehicle traffic.

Table 7. Estimated coefficients and t values for different combinations of movements preceding collisions. Note: these estimates are in a continued showcase of the MNL model results shown in Table 6.

Independent Variables		**Dependent Variable:** Collision Severity Ref. level: Injury (Complaint of Pain)							
		Pedestrian Model				**Bicyclist Model**			
		Coef. & t-value			*Obs. Count*	*Coef. & t-value*			*Obs. Count*
		Injury (Other Visible)	Injury (Severe)	Fatal		Injury (Other Visible)	Injury (Severe)	Fatal	
Constant		-0.722**	-1.946***	-19.486***	7461	-0.753*	-2.139***	-32.120***	6604
		-0.296	-0.478	-0.278		-0.429	-0.747	-0.262	
VRU's Movement Preceding Collision Ref.: (A) Stopped	(B) Proceeding Straight	-0.259	-0.315	-5.955***	3888	0.624	-0.779	-1.597***	5145
		(0.41)	(0.67)	(0.34)		(0.45)	(0.83)	(0.22)	
	(D) Making Right Turn	-	-	-	-	1.669*	-13.428***	-1.960***	140
		-	-	-		(0.94)	(0.32)	0.00	
	(E) Making Left Turn	-	-	-	-	-15.754***	-11.77	2.612***	340
		-	-	-		(0.31)	(19.50)	(0.40)	
	(F) Making U-Turn	-	-	-	-	16.756***	-11.065***	-0.945***	15
		-	-	-		(0.32)	0.00	0.00	
	(Q) Traveling Wrong Way	-	-	-	-	-0.545	-13.093***	0.827***	276
		-	-	-		(0.78)	(0.48)	(0.26)	
Driver's Movement Preceding Collision Ref.: (A) Stopped	(B) Proceeding Straight	0.722**	1.172**	17.986***	3250	0.984**	0.453	9.296***	2698
		(0.31)	(0.49)	(0.30)		(0.50)	(0.89)	(0.21)	
	(D) Making Right Turn	0.214	-0.052	17.018***	1045	0.635	-0.061	8.602***	1488
		(0.33)	(0.55)	(0.39)		(0.65)	(1.29)	(0.29)	
	(E) Making Left Turn	0.297	0.117	16.938***	2397	1.329**	-0.059	10.765***	1237
		(0.31)	(0.51)	(0.34)		(0.60)	(1.29)	(0.29)	
	(F) Making U-Turn	-16.647***	-12.643***	-4.167***	18	18.454***	-5.308***	-7.528***	76
		(0.55)	0.00	0.00		(0.14)	(0.54)	0.00	
	(G) Backing	-0.346	-0.267	-1.913***	287	0.754	-11.677***	-5.198***	61
		(0.39)	(0.62)	0.00		(1.48)	(0.35)	0.00	
	(H) Slowing / Stopping	-0.377	0.847	-1.250***	60	0.748	-10.393***	7.310***	49
		(0.87)	(0.95)	0.00		(1.48)	(0.43)	(0.40)	
	(J) Changing Lanes	0.719	-13.267***	18.791***	18	10.586***	-0.192	-2.338***	76
		(1.04)	(0.62)	(1.04)		(0.15)	(0.41)	0.00	
	(K) Parking Maneuver	-0.531	-16.961***	-4.149***	27	0.517***	0.042	-3.519***	62
		(0.86)	(0.75)	0.00		(0.16)	(0.55)	0.00	

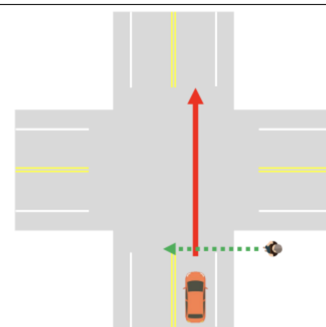
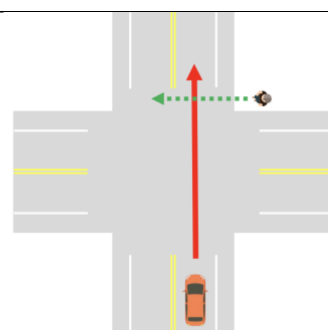
Independent Variables		**Dependent Variable:** Collision Severity Ref. level: Injury (Complaint of Pain)							
		Pedestrian Model				**Bicyclist Model**			
		Coef. & t-value			*Obs. Count*	*Coef. & t-value*			*Obs. Count*
		Injury (Other Visible)	Injury (Severe)	Fatal		Injury (Other Visible)	Injury (Severe)	Fatal	
	(L) Entering Traffic	-0.067	-13.985***	17.089***	90	18.466***	-1.769***	7.293***	177
		(0.62)	(0.36)	(0.90)		(0.38)	(0.45)	0.00	
	(P) Merging	-	-	-	-	-14.175***	-11.687	-1.875***	25
		-	-	-		(0.48)	(58.67)	0.00	
Interaction Terms of Movement Preceding Collision									
Movement of VRU	*Movement of Driver*	Pedestrian Model				Bicyclist Model			
		Coef. & t-value			*Obs. Count*	*Coef. & t-value*			*Obs. Count*
		Injury (Other Visible)	Injury (Severe)	Fatal		Injury (Other Visible)	Injury (Severe)	Fatal	
(B) Proceeding Straight	(B) Proceeding Straight	0.037	-0.121	4.707***	1451	-0.928*	0.711	20.553***	1828
		(0.42)	(0.68)	(0.38)		(0.52)	(0.97)	(0.21)	
(D) Making Right Turn	(B) Proceeding Straight	-	-	-	-	-1.628	13.594***	-2.759***	81
		-	-	-		(1.00)	(0.32)	0.00	
(E) Making Left Turn	(B) Proceeding Straight	-	-	-	-	15.649***	11.805	-7.156***	279
		-	-	-		(0.38)	(19.50)	0.00	
(Q) Traveling Wrong Way	(B) Proceeding Straight	-	-	-	-	0.502	13.044***	19.164***	83
		-	-	-		(0.85)	(0.69)	(0.26)	
(B) Proceeding Straight	(D) Making Right Turn	-0.181	-0.426	3.007***	654	-0.603	0.351	19.373***	1235
		(0.44)	(0.75)	(0.70)		(0.66)	(1.35)	(0.29)	
(D) Making Right Turn	(D) Making Right Turn	-	-	-	-	-1.551	-7.700***	0.968***	28
		-	-	-		(1.12)	0.00	0.00	
(E) Making Left Turn	(D) Making Right Turn	-	-	-	-	15.990***	-14.217***	-3.034***	17
		-	-	-		(0.61)	0.00	0.00	
(Q) Traveling Wrong Way	(D) Making Right Turn	-	-	-	-	0.171	11.709***	-6.775***	118
		-	-	-		(0.94)	(1.08)	0.00	
(B) Proceeding Straight	(E) Making Left Turn	0.06	-0.285	3.876***	1503	-1.143*	1.017	17.422***	1110
		(0.42)	(0.70)	(0.47)		(0.61)	(1.35)	(0.29)	
(E) Making Left Turn	(E) Making Left Turn	-	-	-	-	14.080***	12.022	-5.606***	31
		-	-	-		(0.56)	(19.52)	0.00	
		-	-	-	-	-0.253	12.988***	-3.217***	19

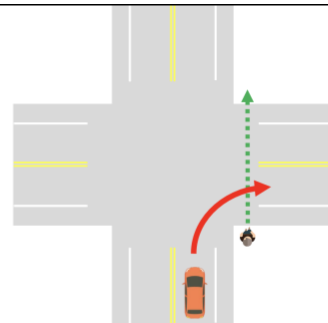
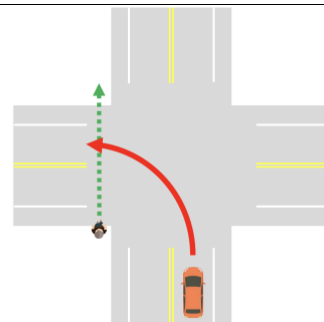
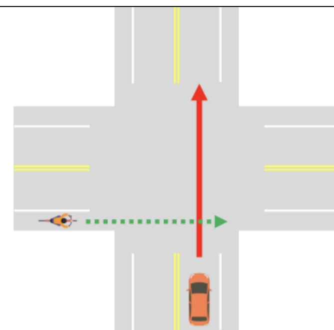
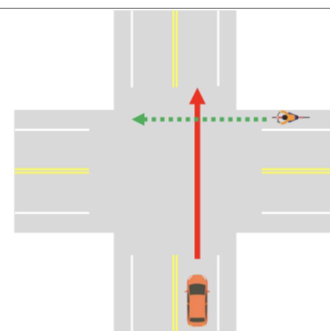
Independent Variables		Dependent Variable: Collision Severity Ref. level: Injury (Complaint of Pain)							
		Pedestrian Model				**Bicyclist Model**			
		Coef. & t-value			*Obs. Count*	*Coef. & t-value*			*Obs. Count*
		Injury (Other Visible)	Injury (Severe)	Fatal		Injury (Other Visible)	Injury (Severe)	Fatal	
(Q) Traveling Wrong Way	(E) Making Left Turn	-	-	-		(1.00)	(1.22)	0.00	
(B) Proceeding Straight	(F) Making U-Turn	-	-	-	-	-18.819***	4.512***	-6.268***	67
		-	-	-		(0.14)	(0.54)	0.00	
(B) Proceeding Straight	(G) Backing	0.295	-1.069	2.791***	101	-0.785	12.398***	-5.593***	53
		(0.53)	(1.06)	0.00		(1.51)	(0.35)	0.00	
(B) Proceeding Straight	(H) Slowing / Stopping	0.26	-12.823***	1.109***	20	-0.182	11.606***	-5.830***	30
		(1.05)	(0.00)	0.00		(1.53)	(0.43)	0.00	
(B) Proceeding Straight	(J) Changing Lanes	-	-	-	-	-9.717***	0.759*	-2.499***	67
		-	-	-		(0.15)	(0.41)	0.00	
(B) Proceeding Straight	(K) Parking Maneuver	-	-	-	-	0.517***	0.042	-3.519***	60
		-	-	-		(0.16)	(0.55)	0.00	
(B) Proceeding Straight	(L) Entering Traffic	0.712	14.588***	5.308***	41	-18.521***	1.811***	5.543***	134
		(0.75)	(0.36)	(1.18)		(0.40)	(0.56)	0.00	
(Q) Traveling Wrong Way	(L) Entering Traffic	-	-	-	-	-17.813***	13.956***	2.038***	33
		-	-	-		(0.64)	(0.80)	0.00	
(B) Proceeding Straight	(P) Merging	-	-	-	-	14.911***	-11.981***	-0.567***	17
		-	-	-		(0.56)	(0.00)	0.00	

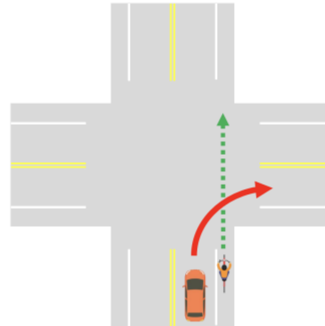
*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 8 enumerates and illustrates the seven typical collision types with different movements preceding collision for VRU and vehicle, accounting for the most VRU-related crashes (52.1% for pedestrian crashes and 77.9% for bicyclist crashes). Type 1-4 are intersection VRU collisions related to pedestrians, and type 5-7 are VRU collisions related to bicyclists. As illustrated by the scenario diagrams, first of all, type 1 and type 5 are similar collision types where thru traffic vehicles have potential collisions with perpendicular VRU flow coming from the near-side crosswalk/bike crossing. Likewise, type 2 and type 6 are similar collision types where thru traffic vehicles have collisions with perpendicular VRU flow coming from the far-side crosswalk/bike crossing. Moreover, type 3 and type 7 are collision types where right-turn vehicles have collisions with parallel pedestrian and bike flow in the same direction, respectively. Lastly, type 4 is the type where left-turn vehicles have collisions with parallel pedestrian flow in the same direction. However, since left-turn vehicles can observe oncoming bicyclists *going straight* in the near lane, the collision chance between them is limited and we do not include a collision type where left-turn vehicles have collisions with oncoming bicycles going straight. We can see from both tables that type 1, 2, 5, and 6 collisions comprise most of the collision movements recorded by the historical crash data, which means that those collision types are of more research interest in the following sub-sections.

Table 8. Combinations of movements preceding collisions.

Scenario No.	VRU Flow	Vehicle Flow	Scenario Diagram
Type 1	Near-side ped (Proceeding Straight)	Thru (Proceeding Straight)	
Type 2	Far-side ped (Proceeding Straight)	Thru (Proceeding Straight)	

Scenario No.	VRU Flow	Vehicle Flow	Scenario Diagram
Type 3	Parallel ped (Proceeding Straight)	Right-turn (Making Right Turn)	
Type 4	Parallel ped (Proceeding Straight)	Left-turn (Making Left Turn)	
Type 5	Near-side bike (Proceeding Straight)	Thru (Proceeding Straight)	
Type 6	Far-side bike (Proceeding Straight)	Thru (Proceeding Straight)	

Scenario No.	VRU Flow	Vehicle Flow	Scenario Diagram
Type 7	Parallel bike (Proceeding Straight)	Right-turn (Making Right Turn)	

Note “near-side” and “far-side” mean that the VRU flow is perpendicular to the vehicle traffic flow and exists at the near-side and far-side crosswalk/bike crossing, respectively.

Micro Level Traffic Simulation Results

The simulation of the four technologies is implemented by SUMO with modified internal junction model. The vehicles, including passenger cars and trucks, are equipped with SSM device and thus the conflicts with VRU in a single execution of simulation can be recorded and exported based on selected TTC thresholds. To be more specific, if the TTC value for a conflict between a vehicle and a VRU is smaller than 1.5 seconds (pre-specified in the previous studies), we count this conflict as a collision.

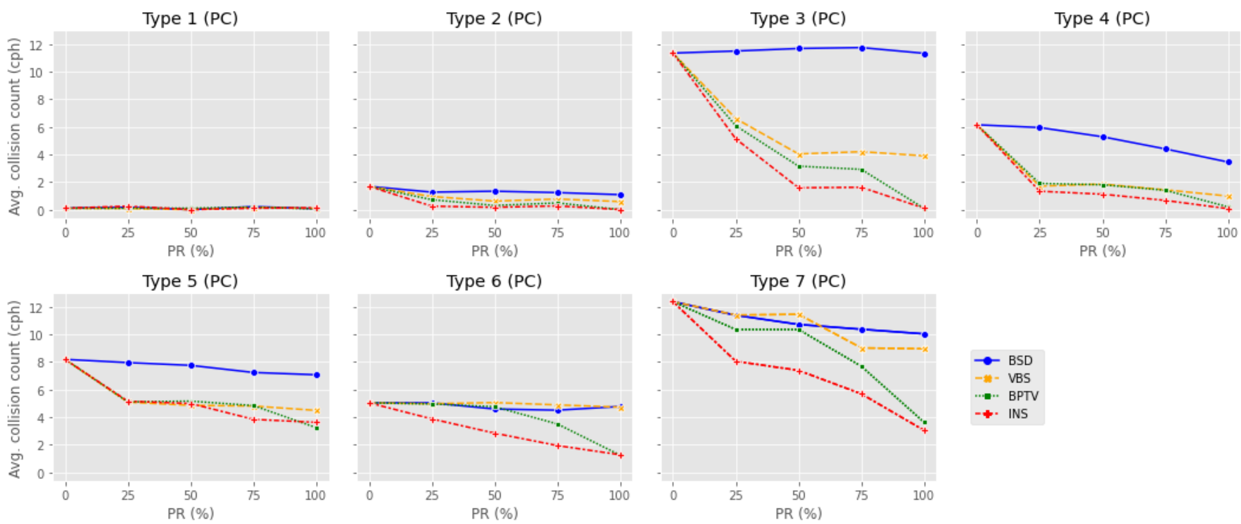
It is important that the randomness of simulation results should be properly addressed and ideally eliminated. To do this, we introduce different random seeds whenever a simulation is initialized. For each of the scenarios, we simulate the seven collision types individually as a single 12-hour simulation for five iterative times. The average collision count over the five iterative times is regarded as the result shown in the following figures. For example, the seven collision types are simulated under no IVT condition, and five iterative simulations are run within each of the types. Hence, there will be a total of 35 times of simulation executions for no IVT condition, generating the average counts of collisions for specific vehicle types (passenger cars and trucks).

Evaluation of Technology Penetration

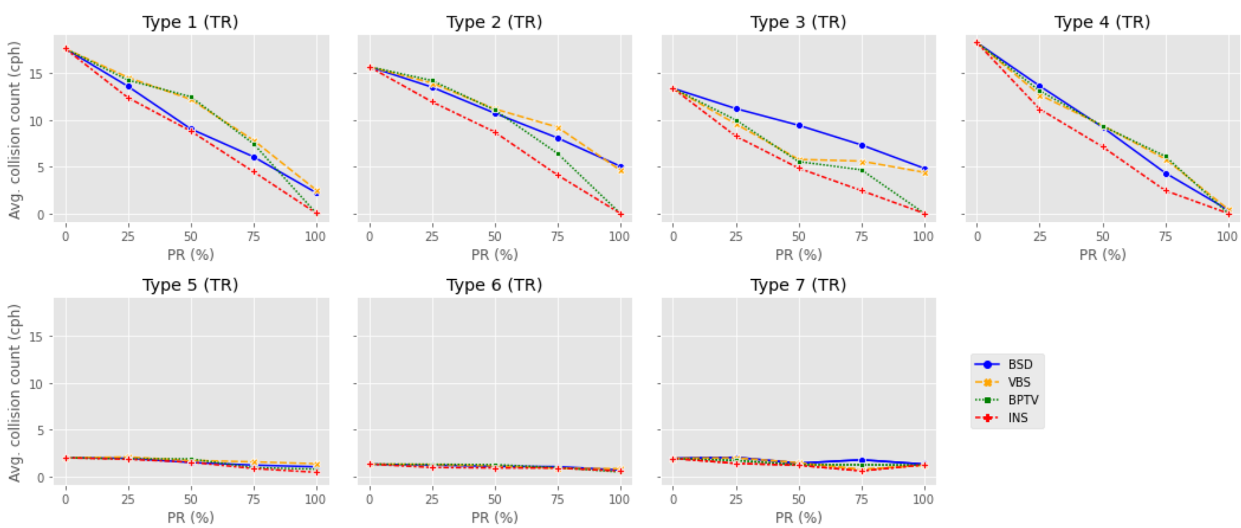
We assess the impact of the penetration level of the various IVT. Four different penetration rates (PR) (25%, 50%, 75% and 100% adoptions) are simulated across the four IVT, where driving without IVT condition can be viewed as 0% PR condition. In each of the simulation settings, the generation of vehicles will proceed randomly, which means the arrival distribution of VRU and vehicles equipped with and without IVT is random. In the following sub-sections, results of the four IVT and two sensitivity tests on sight distance and traffic volume are described and discussed.

IVT simulation

We collect collision count results for both passenger car- and truck-related collisions in simulation and arrange them by the four IVT (namely BSD, VBS, BPTV and INS), the four PR (0%, 25%, 50%, 75% and 100%), as well as the seven collision types. For consistency, we assume that the wireless communication errors do not change by visual acuity and environments, which however may change in the real world due to dense buildings and high usage volume.



a) Passenger cars



b) Trucks

Note: PC=passenger cars; TR=trucks; PR=penetration rate.

Figure 15. Average collision counts versus PR under four IVT conditions.

Figure 15 shows the average collision counts over seven collision types by passenger cars and trucks. We display the results, which are the average collision counts over five iterative times of

12-hour simulation, in seven separate line plots corresponding to the seven collision types. Among the line plots, the vertical axes represent the collision counts and the horizontal axes represent the five PR adopted, whereas four lines in different colors are drawn within each of the line plots with respect to an IVT of interest.

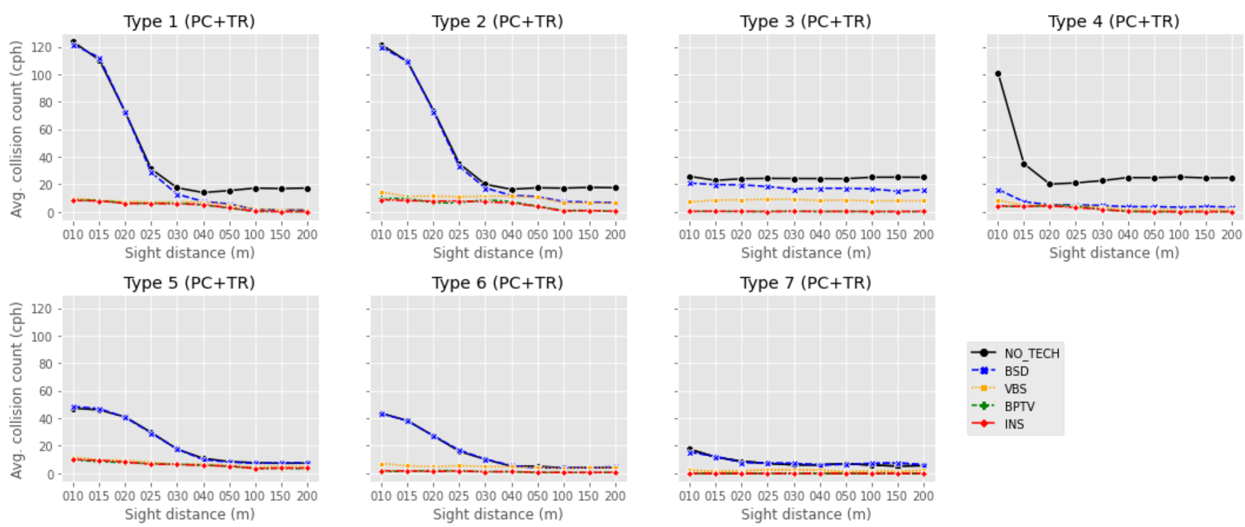
Type 1 and 2 are the crossing collision types where thru traffic vehicles have potential collisions with perpendicular pedestrian flows. Similarly, type 5 and 6 are related to perpendicular bike flows. For type 1 collisions, besides low collision counts which are below 0.5 collision per hour (cph) for passenger cars, no obvious changes in collision counts are found as the PR of any of the IVT increases. However, the average collision counts for trucks reduce by 87.5%, 85.9%, and even 100% as BSD, VBS and BPTV/INS are fully adopted, respectively. For type 2 collisions, the average collision count for passenger cars under BPTV and INS conditions drop to below 0.2 cph as the PR increase to 100%. Likewise, the reductions for trucks on 100% PR of the four IVT are 67.9%, 70.6%, 100% and 100%, respectively. For type 5 collisions, the reduction rates of average collision counts for passenger cars are 13.6%, 45.2%, 60.5% and 55.8% as four IVT are fully adopted orderly. The reduction rates for truck collisions are also similar, as collisions cannot be 100% eliminated by IVT. This situation is the same on type 6 collisions, where full BPTV can reduce average counts of collisions by 75.5% and 64.9% for passenger cars and trucks.

Type 3, 4 and 7 are the crossing collision types where turning vehicles collide with oncoming VRU going straight. For type 3 passenger-car collisions, 100% adoption of VBS, BPTV and INS can reduce the average collision counts by 65.6%, 99.3% and 99.1%, respectively, while BSD seems not to reduce type 3 collisions. Besides the similar safety improvement effects of VBS, BPTV and INS on truck collisions, BSD can reduce 64.0% of truck collisions. For type 4 collisions, the reduction rates on passenger-car collisions by the four 100% IVT are 43.9%, 84.0%, 96.7% and 98.9%, respectively. Similar reduction rates exist on truck collisions. Reduction on passenger-car collision counts of type 4 and type 7 is different from those of type 3. Although similar reduction pattern persists, the average collision counts cannot be eliminated as 100% INS is deployed, returning 75.5% and 36.0% of reduction rates for passenger cars and trucks, respectively.

From Figure 15, there are three major findings as are summarized below. Firstly, it seems no IVT can significantly reduce type 1 VRU collisions, as no direct evidence can be found in the simulation. The reason may be that the probability of type 1 collisions at 0% PR is already very low, and thus no obvious trends of safety improvement can be observed when adopting IVT. In addition, due to the complexity of the inherent simulation mechanism of SUMO, the reasons why 0% PR does not collide can be diverse. We speculate that one of the reasons may be that in the case of Type 1, the vehicle driver has a good view, and enough sight distance and pedestrians can stop immediately with a deceleration of $9.8 m/s^2$ (Rothenbücher et al. 2016), thus avoiding most collisions. This also explains why the type 5 has higher collision counts, because bicycle has a lower deceleration compared to a pedestrian in our simulation settings. Secondly, in the collision scenarios of type 3, 4, and 7, BSD has the worst effect on car collision reduction among the four technologies, while INS and BPTV can reduce most of the collisions at 100% PR. However, even if all VBS technology is adopted, only 40-60% of collision accidents can be avoided. This may indicate that in our simulation settings, BPTV and INS can avoid most VRU accidents by virtue of their two-way communication advantages. Lastly, we want to focus on the low PR situation and compare the differences between the four IVT, and we found that for type 2-7 collisions, INS can have the best collision reduction effect under the condition of 25% PR, and the reduction is at least 35% or more. This finding shows that compared to BPTV, INS can achieve a better collision reduction effect because it has a central sensing module to detect objectives near an intersection, which is not dependent on either vehicles or VRU are equipped with specific technologies.

Sensitivity test I: sight distance

Supplementary to the four IVT, we test the sight distance in different value settings under no IVT condition and other four IVT. As is suggested by the previous MNL modeling results that lighting and weather, which can result in low sight distance naturally, can be factors affecting the severity of VRU collisions, we put the sight distance into interest. Since the simulation of the four IVT is based on the condition of good sight distance at daytime, we set the sight distance as a variable for sensitivity testing, where we can simulate the situation of poor sight distance at night as well. The sight distance in the sensitivity test is divided into eight groups, which are 10m, 15m, 20m, 25m, 30m, 40m, 50m, 100m, 150m and 200m. Also, the average collision counts are obtained by averaging the results of five iterative times of 12-hour simulation in SUMO.



Note: PC=passenger cars; TR=trucks.

Figure 16. Average collision counts versus sight distance under five IVT adoption conditions.

Figure 16 shows the average collision counts for both passenger cars and trucks under different settings of sight distance. In each of the line plots, the horizontal axis represents sight distance, and the vertical axis represents average collision count across the five IVT adoption conditions. The influence of sight distance on collision types 1, 2, 5, and 6 is similar. In the absence of IVT (driving without IVT), when the sight distance is less than 30 m, the average collision counts will increase significantly to over 60 cph. For these four types of collisions, the data points of BSD are almost the same as those of no IVT condition, and it can be considered that it does not help to improve the safety of VRU. In contrast, VBS, BPTV and INS can significantly reduce the collision counts in the conditions of sight distance below 30 m, due to their features of human-vehicle communication. Therefore, these three technologies can well improve the VRU traffic safety under low sight distance conditions for the four types of collisions. As for type 3, 4, and 7, the turning collisions, we found that the situation is more complicated.

The impact threshold of sight distance on collision count under no IVT condition is approximately 20 m, which is lower than the threshold for the aforementioned collision types. Also, BSD has a moderate effect on reducing collision count for type 4 left-turn collisions, while it does not show any effect on improving safety for right-turn collisions. Overall, all collision types begin to stabilize after the sight distance exceeds 30 m, while most of the collision types still have over 50 collision counts. When BPTV/INS is 100% adopted, we can see that at the 10m sight distance, the average collision counts of most collision types have significant drops, and the maximum drop is 99.9% of type 4. As the sight distance increases, the collision counts are basically stable below 5 (except for type 5), which means that INS can improve the VRU safety regardless of sight distance.

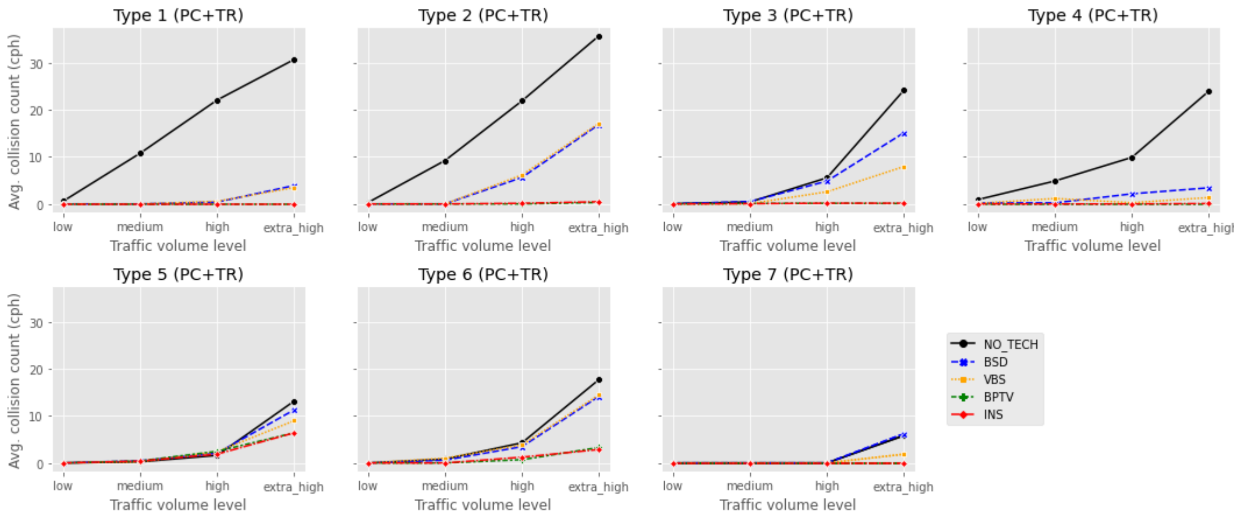
Sensitivity test II: traffic volume

Another sensitivity test needed to be implemented in our project is regarding traffic volume of VRU and vehicles, because the traffic volume settings in the previous simulations are arbitrary in order to simulate collisions in the baseline (no IVT) condition. However, in the real world, how do we choose the best IVT in terms of safety improvement and cost of installation under different traffic volume conditions? It is important for the simulation to answer such a question. In this sensitivity test, four different levels of traffic volume conditions are specified in Table 9.

Table 9. Settings of traffic volumes for both VRU and vehicles in sensitivity test II (unit: veh/h).

Collision types	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7
VRU traffic volume	200; 400; 600;800	200; 400; 600;800	200; 400; 600;800	200; 400; 600;800	100; 200; 300; 400	100; 200; 300; 400	100; 200; 300; 400
Passenger car traffic volume	200; 400; 600; 800	200; 400; 600; 800	100; 200; 300; 400	100; 200; 300; 400	200; 400; 600; 800	200; 400; 600; 800	100; 200; 300; 400
Truck traffic volume	20; 40; 60; 80	20; 40; 60; 80	10; 20; 30; 40	10; 20; 30; 40	20; 40; 60; 80	20; 40; 60; 80	10; 20; 30; 40

Note: four values in each of the cells represent four traffic volume levels, namely low, medium, high and extremely high.



Note: PC=passenger cars; TR=trucks; extra_high= extremely high traffic volume condition.

Figure 17. Average collision counts versus four traffic volume level conditions.

Figure 17 shows the average collision counts over the four levels of traffic volume settings under five different IVT adoption conditions. Results suggest that regardless of IVT, the average collision counts are almost zero in the low traffic condition, but then increase significantly as the traffic volume increases. Among them, the collision types related to the thru-traffic vehicles have higher collision counts in high-volume scenarios. Horizontally comparing the impact of the four IVT on the reduction of the collision count under different scenarios, we find that BSD has the most moderate effect of collision reduction on all collision types under the four traffic conditions, while it has certain effect of collision reduction on type 3, 4 and 7. BPTV and INS were the most effective techniques for reducing collision counts among the four IVT, which have anticipated effects under high traffic volume scenarios with the ability to eliminate most collisions when they are 100% adopted. Also, it cannot be ignored that these two IVT cannot eliminate collisions in extreme high traffic scenarios, but can only reduce them to low levels. We speculate that the ultimate reason is that, among types with large relative speeds at the time of collision (i.e., type 1, 2, 5, and 6), even the INS cannot handle communication in time to give the conflicting parties enough time to take actions.

Conclusion

In order to know how different IVT will affect VRU' safety in different environmental and system conditions (e.g., sight distance and traffic volume) at signalized intersections, we combine aggregate historical crash data analysis and micro transportation simulation to examine the safety impacts of four different IVT. Most importantly, we develop an empirical microsimulation tool to quantify the safety Impacts of these IVT on VRU.

In the statistical analysis on the historical crash data, this study identifies key factors for injury severity for VRU-related crashes at signalized intersections in California cities. MNL models are performed on the injury severity variable. The regression results show that: 1) the severity of pedestrian accidents (not divided by movement scenarios) in rainy weather is unlikely to increase, and the OR of the severity of bicycle accidents does not change significantly. Compared to pedestrian accidents where vehicles go straight, and only the OR of visible injury is reduced, in right-turn accidents the OR of severe and fatal accidents in is significantly reduced. 2) the model results show that the OR of severe or fatal accidents between pedestrians and bicycles is significantly positive when the accident is at night but with streetlights compared to daytime, which means that a lack of light increases the possibility of severe accidents for pedestrians and bicycles. 3) in terms of demographics, the results show that male and at-fault attributes are the main factors that increase the severity of VRU accidents, and VRU accidents in the high age group are more likely to be fatal. Most importantly, we model the interaction terms of movement combinations preceding collision to propose the seven typical collision types for both pedestrians and bicyclists, which supports the micro simulation part.

In terms of the micro traffic simulation in SUMO, we extract four major findings from the results of average collision counts that come from five iterative 12-hour simulations, including: 1) INS is empowered to be the most efficient technology to significantly reduce average collision counts for passenger cars under type 3, 4 and 7 (turning movements) collisions; 2) BSD has the most minimal effects on those types, with the least reductions on average collision counts observed; 3) All IVT can help improve truck-related VRU crash safety for pedestrians (type 1-4); and 4) BPTV and INS can reach 100% collision reduction while BSD and VBS have less significant effects. Also, two sensitivity tests are performed regarding sight distance and traffic flow. For the sensitivity test I, "distance threshold" where the average collision count does not decrease as sight distance increases exists for most collision types except for type 3, and thru-traffic collision types (1, 2, 5 and 6) have higher distance threshold than turning collision types. INS and BPTV have significant collision reduction effects in low sight distance conditions. For the sensitivity test II, INS and BPTV can reduce 100% collisions from medium to extremely high traffic conditions for type 1-4 and 7. In type 5 and 6, INS and BPTV can only reduce around 50% of collision at extremely high traffic conditions.

Overall, our research develops a novel traffic safety evaluation framework, which is based on mirroring real-world vision acuity and IVT implementation. Our simulation results also find the best working condition (e.g., sight distance, traffic volume, and intersection shape) for four different IVT. The analysis of these technologies can help both public and related stakeholders to better understand how different IVT will improve the safety of cyclists and pedestrians under various conditions at intersections. The research could inform state agencies such as Caltrans, and local (metropolitan) planning organizations about how to develop various IVT and would have implications for improving the mobility of people and goods.

Reference

Alshehri, Abdulaziz, Deogratias Eustace, and Peter Hovey. 2020. "Analysis of Factors Affecting Crash Severity of Pedestrian and Bicycle Crashes Involving Vehicles at Intersections," August, 49–58. https://doi.org/10.1061/9780784483152.005.

Anaya, J. J., P. Merdrignac, O. Shagdar, F. Nashashibi, and J. E. Naranjo. 2014. "Vehicle to Pedestrian Communications for Protection of Vulnerable Road Users." In *2014 IEEE Intelligent Vehicles Symposium Proceedings*, 1037–42. https://doi.org/10.1109/IVS.2014.6856553.

Astarita, Vittorio, Vincenzo Pasquale Giofrè, Giuseppe Guido, and Alessandro Vitale. 2021. "A Review of the Use of Traffic Simulation for the Evaluation of Traffic Safety Levels: Can We Use Simulation to Predict Crashes?" *Transportation Research Procedia*, 23rd EURO Working Group on Transportation Meeting, EWGT 2020, 16-18 September 2020, Paphos, Cyprus, 52 (January): 244–51. https://doi.org/10.1016/j.trpro.2021.01.028.

Bachmann, M., M. Morold, and K. David. 2020. "On the Required Movement Recognition Accuracy in Cooperative VRU Collision Avoidance Systems." *IEEE Transactions on Intelligent Transportation Systems*, 1–10. https://doi.org/10.1109/TITS.2020.2976593.

Barnett, J., N. Gizinski, E. Mondragon-Parra, J. E. Siegel, D. Morris, T. Gates, E. Kassens-Noor, and P. Savolainen. 2020. "Automated Vehicles Sharing the Road: Surveying Detection and Localization of Pedalcyclists." *IEEE Transactions on Intelligent Vehicles*, 1–1. https://doi.org/10.1109/TIV.2020.3046859.

"Can Data Generated by Connected Vehicles Enhance Safety?: Proactive Approach to Intersection Safety Management - Mohsen Kamrani, Behram Wali, Asad J. Khattak, 2017." n.d. Accessed January 20, 2021. https://journals.sagepub.com/doi/abs/10.3141/2659-09.

Chang, Shun-Hui, Chih-Yung Lin, Chun-Chia Hsu, Chin-Ping Fung, and Jiun-Ren Hwang. 2009. "The Effect of a Collision Warning System on the Driving Performance of Young Drivers at Intersections." *Transportation Research Part F: Traffic Psychology and Behaviour* 12 (5): 371–80. https://doi.org/10.1016/j.trf.2009.05.001.

Clark, David E., and Brad M. Cushing. 2004. "Rural and Urban Traffic Fatalities, Vehicle Miles, and Population Density." *Accident Analysis & Prevention* 36 (6): 967–72. https://doi.org/10.1016/j.aap.2003.10.006.

Coeckelbergh, Tanja R. M., Wiebo H. Brouwer, Frans W. Cornelissen, Peter van Wolffelaar, and Aart C. Kooijman. 2002. "The Effect of Visual Field Defects on Driving Performance: A Driving Simulator Study." *Archives of Ophthalmology* 120 (11): 1509–16. https://doi.org/10.1001/archopht.120.11.1509.

Dasanayaka Nishanthi, Hasan Khondokar Fida, Wang Charles, and Feng Yanming. 2020. "Enhancing Vulnerable Road User Safety: A Survey of Existing Practices and Consideration for Using Mobile Devices for V2X Connections," October. https://arxiv.org/abs/2010.15502v1.

Dhondge, K., S. Song, B. Choi, and H. Park. 2014. “WiFiHonk: Smartphone-Based Beacon Stuffed WiFi Car2X-Communication System for Vulnerable Road User Safety.” In *2014 IEEE 79th Vehicular Technology Conference (VTC Spring)*, 1–5. https://doi.org/10.1109/VTCSpring.2014.7023146.

Djamel, Bektache, Yakoubi Mohamed Amine, and Ghoualmi Nacera zine. 2020. “Forecasting Approach for Blind Spot Collision Alert.” In *Proceedings of the 10th International Conference on Information Systems and Technologies*, 1–5. ICIST ’20. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3447568.3448520.

Doniec, Arnaud, René Mandiau, Sylvain Piechowiak, and Stéphane Espié. 2008. “A Behavioral Multi-Agent Model for Road Traffic Simulation.” *Engineering Applications of Artificial Intelligence* 21 (8): 1443–54. https://doi.org/10.1016/j.engappai.2008.04.002.

Ellen, Christopher, Dante Pace, and Sunghoon Yoon. 2015. “IntelliWay: Connecting Bicycles to the V2V Network.” *Major Qualifying Projects (All Years)*, December. https://digitalcommons.wpi.edu/mqp-all/2466.

Fitah, A., A. Badri, M. Moughit, and A. Sahel. 2018. “Performance of DSRC and WIFI for Intelligent Transport Systems in VANET.” *Procedia Computer Science*, PROCEEDINGS OF THE FIRST INTERNATIONAL CONFERENCE ON INTELLIGENT COMPUTING IN DATA SCIENCES, ICDS2017, 127 (January): 360–68. https://doi.org/10.1016/j.procs.2018.01.133.

Gattis, J. L., and Sonny T. Low. 1998. “Intersection Angle Geometry and the Driver’s Field of View.” *Transportation Research Record* 1612 (1): 10–16. https://doi.org/10.3141/1612-02.

Habibovic, Azra, and Johan Davidsson. 2012a. “Causation Mechanisms in Car-to-Vulnerable Road User Crashes: Implications for Active Safety Systems.” *Accident Analysis & Prevention*, PTW + Cognitive impairment and Driving Safety, 49 (November): 493–500. https://doi.org/10.1016/j.aap.2012.03.022.

———. 2012b. “Causation Mechanisms in Car-to-Vulnerable Road User Crashes: Implications for Active Safety Systems.” *Accident Analysis & Prevention*, PTW + Cognitive impairment and Driving Safety, 49 (November): 493–500. https://doi.org/10.1016/j.aap.2012.03.022.

Hammoud, Riad I. 2008. *Passive Eye Monitoring: Algorithms, Applications and Experiments*. Springer Science & Business Media.

Hasani, Mahdie, Arash Jahangiri, Ipek Nese Sener, Sirajum Munira, Justin M. Owens, Bruce Appleyard, Sherry Ryan, Shawn M. Turner, and Sahar Ghanipoor Machiani. 2019. “Identifying High-Risk Intersections for Walking and Bicycling Using Multiple Data Sources in the City of San Diego.” Research Article. Journal of Advanced Transportation. Hindawi. June 16, 2019. https://doi.org/10.1155/2019/9072358.

Heinovski, J., L. Stratmann, D. S. Buse, F. Klingler, M. Franke, M. H. Oczko, C. Sommer, I. Scharlau, and F. Dressler. 2019. “Modeling Cycling Behavior to Improve Bicyclists’ Safety at Intersections - A Networking Perspective.” In *2019 IEEE 20th International Symposium on “A World of Wireless, Mobile and Multimedia Networks” (WoWMoM)*, 1–8. https://doi.org/10.1109/WoWMoM.2019.8793008.

Hisaka, S., and S. Kamijo. 2011. “On-Board Wireless Sensor for Collision Avoidance: Vehicle and Pedestrian Detection at Intersection.” In *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 198–205. https://doi.org/10.1109/ITSC.2011.6082853.

Hussain, Qinaat, Mustafa Almallah, Wael K. M. Alhajyaseen, and Charitha Dias. 2020. “Impact of the Geometric Field of View on Drivers’ Speed Perception and Lateral Position in Driving Simulators.” *Procedia Computer Science*, The 11th International Conference on Ambient Systems, Networks and Technologies (ANT) / The 3rd International Conference on Emerging Data and Industry 4.0 (EDI40) / Affiliated Workshops, 170 (January): 18–25. https://doi.org/10.1016/j.procs.2020.03.005.

Hyun, E., Y. S. Jin, and J. H. Lee. 2017. “Design and Development of Automotive Blind Spot Detection Radar System Based on ROI Pre-Processing Scheme.” *International Journal of Automotive Technology* 18 (1): 165–77. https://doi.org/10.1007/s12239-017-0017-5.

Jenkins, M., D. Duggan, and A. Negri. 2017. “Towards a Connected Bicycle to Communicate with Vehicles and Infrastructure : Multimodel Alerting Interface with Networked Short-Range Transmissions (MAIN-ST).” In *2017 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, 1–3. https://doi.org/10.1109/COGSIMA.2017.7929602.

Ke, Ruimin, Jerome Lutin, Jerry Spears, and Yinhai Wang. 2017. “A Cost-Effective Framework for Automated Vehicle-Pedestrian Near-Miss Detection Through Onboard Monocular Vision.” In , 25–32. https://openaccess.thecvf.com/content_cvpr_2017_workshops/w9/html/Ke_A_Cost-Effective_Framework_CVPR_2017_paper.html.

Kedowide, Colombiano, Charles Gouin-Vallerand, and Evelyne Vallieres. 2014. “Recognizing Blind Spot Check Activity with Car Drivers Based on Decision Tree Classifier Approach.” In *Workshops at the Twenty-Eighth AAAI Conference on Artificial Intelligence*. https://www.aaai.org/ocs/index.php/WS/AAAIW14/paper/view/8822.

Kitajima, Sou, Keisuke Shimono, Jun Tajima, Jacobo Antona-Makoshi, and Nobuyuki Uchida. 2019. “Multi-Agent Traffic Simulations to Estimate the Impact of Automated Technologies on Safety.” *Traffic Injury Prevention* 20 (sup1): S58–64. https://doi.org/10.1080/15389588.2019.1625335.

Krajzewicz, Daniel, and Jakob Erdmann. 2013. “Road Intersection Model in SUMO.” In *1st SUMO User Conference - SUMO 2013*, 21:212–20. Berlin, Germany: DLR. http://sumo-sim.org/2013/conference.html.

Larish, John F., and John M. Flach. 1990. “Sources of Optical Information Useful for Perception of Speed of Rectilinear Self-Motion.” *Journal of Experimental Psychology: Human Perception and Performance* 16 (2): 295–302. https://doi.org/10.1037/0096-1523.16.2.295.

Li, C., G. Salinas, P. Huang, G. Tu, G. Hsu, and T. Hsieh. 2018. “V2PSense: Enabling Cellular-Based V2P Collision Warning Service through Mobile Sensing.” In *2018 IEEE International Conference on Communications (ICC)*, 1–6. https://doi.org/10.1109/ICC.2018.8422981.

Liu, G., L. Wang, and S. Zou. 2017. "A Radar-Based Blind Spot Detection and Warning System for Driver Assistance." In *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2204–8. https://doi.org/10.1109/IAEAC.2017.8054409.

Liu, Kaiqi, Wenguang Wang, and Jun Wang. 2019. "Pedestrian Detection with Lidar Point Clouds Based on Single Template Matching." *Electronics* 8 (7): 780. https://doi.org/10.3390/electronics8070780.

Liu, W., S. Muramatsu, and Y. Okubo. 2018. "Cooperation of V2I/P2I Communication and Roadside Radar Perception for the Safety of Vulnerable Road Users." In *2018 16th International Conference on Intelligent Transportation Systems Telecommunications (ITST)*, 1–7. https://doi.org/10.1109/ITST.2018.8566704.

Milch, S., and M. Behrens. 2001. *Pedestrian Detection with Radar and Computer Vision*.

Montella, Alfonso, Carmen Guida, Jlenia Mosca, Jaeyoung Lee, and Mohamed Abdel-Aty. 2020. "Systemic Approach to Improve Safety of Urban Unsignalized Intersections: Development and Validation of a Safety Index." *Accident Analysis & Prevention* 141 (June): 105523. https://doi.org/10.1016/j.aap.2020.105523.

Munira, Sirajum, Ipek N. Sener, and Boya Dai. 2020. "A Bayesian Spatial Poisson-Lognormal Model to Examine Pedestrian Crash Severity at Signalized Intersections." *Accident Analysis & Prevention* 144 (September): 105679. https://doi.org/10.1016/j.aap.2020.105679.

NHTSA. 2017. "Traffic Safety Facts Annual Report Tables." https://cdan.nhtsa.gov/tsftables/tsfar.htm.

———. 2018. "Summary of Motor Vehicle Crashes." https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812580.

"OTS Crash Rankings | Office of Traffic Safety." n.d. Accessed April 20, 2021. https://www.ots.ca.gov/media-and-research/crash-rankings/.

Ouni, Fedy, and Mounir Belloumi. 2018. "Spatio-Temporal Pattern of Vulnerable Road User's Collisions Hot Spots and Related Risk Factors for Injury Severity in Tunisia." *Transportation Research Part F: Traffic Psychology and Behaviour* 56 (July): 477–95. https://doi.org/10.1016/j.trf.2018.05.003.

Patil, Ajaykumar. 2016a. "SAFETY ASPECTS OF BICYCLISTS IN A CONNECTED VEHICLE ENVIRONMENT." Thesis. https://rc.library.uta.edu/uta-ir/handle/10106/25831.

———. 2016b. "SAFETY ASPECTS OF BICYCLISTS IN A CONNECTED VEHICLE ENVIRONMENT." Thesis. https://rc.library.uta.edu/uta-ir/handle/10106/25831.

"Pedestrians and Bicyclists." n.d. IIHS-HLDI Crash Testing and Highway Safety. Accessed May 19, 2022. https://www.iihs.org/topics/pedestrians-and-bicyclists.

“Performance and Channel Load Evaluation for Contextual Pedestrian-to-Vehicle Transmissions | Proceedings of the First ACM International Workshop on Smart, Autonomous, and Connected Vehicular Systems and Services.” n.d. Accessed February 2, 2021. https://dl.acm.org/doi/abs/10.1145/2980100.2980103.

Rathi, Ajay K. n.d. *Traffic Simulation by Edward Lieberman 18*.

Robartes, Erin, and T. Donna Chen. 2017a. “The Effect of Crash Characteristics on Cyclist Injuries: An Analysis of Virginia Automobile-Bicycle Crash Data.” *Accident Analysis & Prevention* 104 (July): 165–73. https://doi.org/10.1016/j.aap.2017.04.020.

———. 2017b. “The Effect of Crash Characteristics on Cyclist Injuries: An Analysis of Virginia Automobile-Bicycle Crash Data.” *Accident Analysis & Prevention* 104 (July): 165–73. https://doi.org/10.1016/j.aap.2017.04.020.

Robartes, Erin, and T. Donna Chen. 2018. “Crash Histories, Safety Perceptions, and Attitudes among Virginia Bicyclists.” *Journal of Safety Research* 67 (December): 189–96. https://doi.org/10.1016/j.jsr.2018.10.009.

Rothenbücher, Dirk, Jamy Li, David Sirkin, Brian Mok, and Wendy Ju. 2016. “Ghost Driver: A Field Study Investigating the Interaction between Pedestrians and Driverless Vehicles.” In *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 795–802. https://doi.org/10.1109/ROMAN.2016.7745210.

Silla, Anne, Lars Leden, Pirkko Rämä, Johan Scholliers, Martijn Van Noort, and Daniel Bell. 2017. “Can Cyclist Safety Be Improved with Intelligent Transport Systems?” *Accident Analysis & Prevention*, Improving cyclist safety through scientific research, ICSC2015., 105 (August): 134–45. https://doi.org/10.1016/j.aap.2016.05.003.

Silla, Anne, Pirkko Rämä, Lars Leden, Martijn van Noort, Janiek de Kruijff, Daniel Bell, Andrew Morris, Graham Hancox, and Johan Scholliers. 2017. “Quantifying the Effectiveness of ITS in Improving Safety of VRUs.” *IET Intelligent Transport Systems* 11 (3): 164–72. https://doi.org/10.1049/iet-its.2016.0024.

Wang, Kai, Tanmoy Bhowmik, Shamsunnahar Yasmin, Shanshan Zhao, Naveen Eluru, and Eric Jackson. 2019. “Multivariate Copula Temporal Modeling of Intersection Crash Consequence Metrics: A Joint Estimation of Injury Severity, Crash Type, Vehicle Damage and Driver Error.” *Accident Analysis & Prevention* 125 (April): 188–97. https://doi.org/10.1016/j.aap.2019.01.036.

Wu, Bing-Fei, Hao-Yu Huang, Chao-Jung Chen, Ying-Han Chen, Chia-Wei Chang, and Yen-Lin Chen. 2013. “A Vision-Based Blind Spot Warning System for Daytime and Nighttime Driver Assistance.” *Computers & Electrical Engineering*, Special issue on Image and Video Processing, 39 (3): 846–62. https://doi.org/10.1016/j.compeleceng.2013.03.020.

Wu, Kun-Feng, Muhammad Nashir Ardiansyah, and Wei-Jyun Ye. 2018. “An Evaluation Scheme for Assessing the Effectiveness of Intersection Movement Assist (IMA) on Improving Traffic Safety.” *Traffic Injury Prevention* 19 (2): 179–83. https://doi.org/10.1080/15389588.2017.1363891.

Yoon, Shawn, Dante A Pace, and Christopher M Ellen. n.d. “IntelliWay: Connecting Bicycles to the V2V Network,” 60.

Yue, Lishengsa, Mohamed Abdel-Aty, Yina Wu, Jinghui Yuan, and Morgan Morris. 2020. “Influence of Pedestrian-to-Vehicle Technology on Drivers’ Response and Safety Benefits Considering Pre-Crash Conditions.” *Transportation Research Part F: Traffic Psychology and Behaviour* 73 (August): 50–65. https://doi.org/10.1016/j.trf.2020.06.012.

Z., Hassan, Adnan. 2020. “Vehicle Blind Spot Monitoring Phenomenon Using Ultrasonic Sensor.” *International Journal of Emerging Trends in Engineering Research* 8 (8): 4357–65. https://doi.org/10.30534/ijeter/2020/50882020.

Zhao, Junxuan, Hao Xu, Hongchao Liu, Jianqing Wu, Yichen Zheng, and Dayong Wu. 2019. “Detection and Tracking of Pedestrians and Vehicles Using Roadside LiDAR Sensors.” *Transportation Research Part C: Emerging Technologies* 100 (March): 68–87. https://doi.org/10.1016/j.trc.2019.01.007.

Zheng, W., A. Ali, N. González-Prelcic, R. W. Heath, A. Klautau, and E. M. Pari. 2020. “5G V2X Communication at Millimeter Wave: Rate Maps and Use Cases.” In *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, 1–5. https://doi.org/10.1109/VTC2020-Spring48590.2020.9128612.

Data Summary

Products of Research

The data used in this project for macroscopic statistical modeling include the following:

1) OTS crash ranking data

   The California Office of Traffic Safety (OTS) provides a crash ranking dataset which were developed so that individual cities could compare their traffic safety statistics to those of other cities with similar-sized populations. The OTS crash rankings are based on the Empirical Bayesian Ranking Method, which adds weights to different crash statistical categories including observed crash counts, population and daily vehicle miles traveled. In addition, the OTS crash rankings include different types of crashes with larger percentages of total victims and areas of focus for the OTS grant program. In conjunction with the research context, two types of crash rankings are focused on: pedestrians and bicyclists. The original OTS crash rankings for all incorporated cities in California can be accessed at https://www.ots.ca.gov/media-and-research/crash-rankings-results/.

2) SWITRS crash data

   The Transportation Injury Mapping System (TIMS) provides quick, easy, and free access to California crash data provided by the Statewide Integrated Traffic Records System (SWITRS). The crash data includes bicycle and pedestrian collisions with vehicles resulting in injuries from 2014 to 2018. This crash database also provides detailed accident reports including information on casualties, vehicle mode, accident reason, accident location, and road condition. From this crash information, we selected crashes between vehicles and VRUs at signalized intersections, which is the scope of this study. TIMS can be accessed at https://tims.berkeley.edu/.

Data Format and Content

The database used in the project contains two parts: OTS crash rankings and crash data:

- OTS crash rankings: The dataset was created in python using web-scraping technique. The rankings are provided in .csv format.
- Historical crash data: The crash data were accessed from SWITRS. The data for each city selected from OTS crash rankings are stored in three separate files: Collisions.csv, Parties.csv, and Victims.csv.

Data Access and Sharing

The data used for this project is publicly available at https://doi.org/10.25338/B8234N, and no commitment is required from the companies. However, use of the data will follow the restrictions of the corresponding agencies. The modification to the SUMO (traffic simulation software) source code are also available at https://doi.org/10.25338/B8234N—to replicate this study, users will need to download and run the modified code.

Reuse and Redistribution

All Principal Investigators and the project research team have the right to manage the data. The OTS crash ranking data and the historical crash data in California are publicly accessible; users should refer to the original URLs (see Products of Research, above). Users of the modified SUMO source code should use the following suggested citation:

> Xiao, Ivan Runhua; Qian, Xiaodong (2022), Analysis of intelligent vehicle technologies to improve vulnerable road users safety at signalized intersections, Dryad, Dataset, https://doi.org/10.25338/B8234N