

## References

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**Brad’s Notes:** Too Old

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**Brad’s Notes:** Too Old

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Alrefaie, Mohamed Taher, Stever Summerskill, and Thomas W Jackson. "In a heart beat: Using driver's physiological changes to determine the quality of a takeover in highly automated vehicles." *Accident Analysis & Prevention* 131 (2019): 180–190.

**Suggestions for Future Research:** As identified through the literature review of this study, there are some factors affecting response time and quality such as fatigue (Driver, 2014), age (Körber et al., 2016), traffic density (Christian Gold et al., 2016), weather conditions (Louw et al., 2016) and driving experience (Larsson et al., 2014). Those variables were not taken into consideration due to the limitations of the study; however, it should be considered for future work. Additionally, future work will need to recruit different age groups which was identified by others as a critical variable in driver's performance in highly automated driving. Finally, the study acknowledges the limited effort placed on comparing PerSpeed and PerAngle with other measures that were surveyed and introduced in Radlmayr's et al., (2019) comprehensive study. The comparison between TOPS model and their affiliated vehicle-based performance measure would be a great contribution to the research of highly automated vehicles.  
doi:<https://doi.org/10.1016/j.aap.2019.06.011>. <https://www.sciencedirect.com/science/article/pii/S0001457518311217>.

**Brad's Notes:** Not our data.

Alvaro, Pasquale K., Nicole M. Burnett, Gerard A. Kennedy, William Yu Xun Min, Marcus McMahon, Maree Barnes, Melinda Jackson, and Mark E. Howard. "Driver education: Enhancing knowledge of sleep, fatigue and risky behaviour to improve decision making in young drivers." *Accident Analysis & Prevention* 112 (2018): 77–83. doi:<https://doi.org/10.1016/j.aap.2017.12.017>. <https://www.sciencedirect.com/science/article/pii/S0001457517304554>.

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**Brad's Notes:** Not our data. Image processing

Amiri, Amir Mohammadian, Amirhossein Sadri, Navid Nadimi, and Moe Shams. "A comparison between Artificial Neural Network and Hybrid Intelligent Genetic Algorithm in predicting the severity of fixed object crashes among elderly drivers." *Accident Analysis & Prevention* 138 (2020): 105468.

**Suggestions for Future Research:** None

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**Brad's Notes:** Identified factors associated with level of severity of crash.

Arun, Ashutosh, Md Mazharul Haque, Ashish Bhaskar, Simon Washington, and Tarek Sayed. "A systematic mapping review of surrogate safety assessment using traffic conflict techniques." *Accident Analysis & Prevention* 153 (2021): 106016.

**Suggestions for Future Research:** the isolated view of surrogate safety assessment as an objective unto itself has given rise to a lopsided amount of research into the development of novel surrogate measures that at the most provide incremental benefits over traditional ones and less research into critical issues like the development and validation of crash-conflict relationships. The latter, along with the need for surrogate-based crash severity estimation, constitute the most significant lacunae in surrogate assessment and are critical for maturing this approach. Given insights gained into the surrogate framework, it is hoped that future efforts shall focus on focussed research into the specific gaps identified in this study.

doi:<https://doi.org/10.1016/j.aap.2021.106016>. <https://www.sciencedirect.com/science/article/pii/S0001457521000476>.

**Brad's Notes:** Interesting for overview. "Surrogate Safety" is looking for dangerous road conditions without waiting for crashes to occur.

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**Brad's Notes:** Too Old

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**Brad's Notes: Too Old**

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**Brad's Notes:** Interesting. Similar to our data and approach, but with train derailments.

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**Suggestions for Future Research:** In this study, the validation of the research framework is conducted from an experimental perspective. We consider the LC scenario that involve five cars on the highway based on the vehicles’ trajectory dataset collected in the US. To get a stronger validation and evaluation, more research should be conducted to gain further insight into the LC risk. For example, future study can focus on LC risk that involves more vehicle types (e.g. truck, motorcycle, etc.), LC scenarios with more than five vehicles, LC risk on different road types (e.g. urban road), and comparison of LC risk across different countries. Besides vehicle’s behaviors, it shall be useful to investigate human behaviors pertaining to LC risk. The research framework proposed in this paper provides the building blocks in these future studies. From a technical perspective, we could explore more advanced methods to select key features and achieve higher LC risk prediction accuracy. doi:<https://doi.org/10.1016/j.aap.2019.05.017>. <https://www.sciencedirect.com/science/article/pii/S0001457519303860>.

**Brad’s Notes:** Not our data. Interesting in that we could use that data.

Chen, Tianyi, Yiik Diew Wong, Xiupeng Shi, and Yaoyao Yang. “A data-driven feature learning approach based on Copula-Bayesian Network and its application in comparative investigation on risky lane-changing and car-following maneuvers.” *Accident Analysis & Prevention* 154 (2021): 106061.

**Suggestions for Future Research:** Need advanced data cleaning methods , doi:<https://doi.org/10.1016/j.aap.2021.106061>. <https://www.sciencedirect.com/science/article/pii/S0001457521000920>.

**Brad’s Notes:** Used Random Forest in feature selection

Chen, Wei, Krista K. Wheeler, Simon Lin, Yungui Huang, and Huiyun Xiang. “Computerized “Learn-As-You-Go” classification of traumatic brain injuries using NEISS narrative data.” *Accident Analysis & Prevention* 89 (2016): 111–117. doi:<https://doi.org/10.1016/j.aap>.

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**Brad's Notes:** Too Old

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**Brad's Notes:** Too Old

Clarke, David D, Patrick J Ward, and Jean Jones. "Overtaking road-accidents: differences in manoeuvre as a function of driver age1All three authors were working at the University of Nottingham at the time of this work.1." *Accident Analysis & Prevention* 30, no. 4 (1998): 455–467. doi:[https://doi.org/10.1016/S0001-4575\(97\)00105-X](https://doi.org/10.1016/S0001-4575(97)00105-X). <https://www.sciencedirect.com/science/article/pii/S000145759700105X>.

**Brad's Notes:** Too Old

Clarke, David D., Richard Forsyth, and Richard Wright. "A statistical profile of road accidents during cross-flow turns." *Accident Analysis & Prevention* 37, no. 4 (2005): 721–730. doi:<https://doi.org/10.1016/j.aap.2005.03.013>. <https://www.sciencedirect.com/science/article/pii/S0001457505000503>.

**Brad's Notes:** Too Old, Not ML

———. "Behavioural factors in accidents at road junctions: The use of a genetic algorithm to extract descriptive rules from police case files." *Accident Analysis & Prevention* 30, no. 2 (1998): 223–234. doi:[https://doi.org/10.1016/S0001-4575\(97\)00080-8](https://doi.org/10.1016/S0001-4575(97)00080-8). <https://www.sciencedirect.com/science/article/pii/S0001457597000808>.

**Brad's Notes:** Too Old

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**Brad’s Notes:** Too Old

Das, Anik, Mohamed M. Ahmed, and Ali Ghasemzadeh. “Using trajectory-level SHRP2 naturalistic driving data for investigating driver lane-keeping ability in fog: An association rules mining approach.” *Accident Analysis & Prevention* 129 (2019): 250–262. doi:<https://doi.org/10.1016/j.aap.2019.05.024>. <https://www.sciencedirect.com/science/article/pii/S0001457518310182>.

Das, Anik, Md Nasim Khan, and Mohamed M. Ahmed. “Detecting lane change maneuvers using SHRP2 naturalistic driving data: A comparative study machine learning techniques.” *Accident Analysis & Prevention* 142 (2020): 105578.

**Suggestions for Future Research:** While the study exhibited the capability of Machine Learning algorithms to detect lane change maneuvers from the SHRP2 NDS and RID datasets, some limitations should be mentioned. The first limitation is related to the data segmentation approach. The study considered a dynamic segmentation approach to select non-lane change segments. This approach is appropriate and necessary when machine vision-based features (e.g., lane position offset in this study) are included in the dataset. Therefore, the study recommends to use fixed time window approach in the absence of machine vision data in the future. The second limitation is related to the steering wheel angle variable, which was not considered for detecting lane change behavior due to excessive missing values in most of the trips. In addition, data from all surrounding vehicles were not available as front-mounted radar of NDS vehicle cannot detect the presence of vehicles behind the NDS vehicle's lane. Consequently, the lane change was considered as a single behavior of the subject vehicle. Future studies can focus on incorporating data from all surrounding vehicles as the input of the detection algorithm using similar trajectory-level data with information from all surrounding vehicles. Moreover, the study is only limited to trips on freeways. Lane change detection models using the SHRP2 NDS data on urban roadways could be considered in future studies. Furthermore, the continuation of this study is important to include other driver behavioral features in addition to driver demographics in the developed detection algorithm. To be specific, drivers' aggressiveness could be considered in future studies. The lane change events database developed in this study contained a number of features that could be used to classify drivers' aggressiveness. Features associated with driving behavior, such as speed, acceleration, yaw rate, speed differences from speed limit, number of lane changes per mile, etc. could be obtained, and then cluster analysis could be adopted with possible features to classify drivers as aggressive or conservative. Once all drivers are classified, they could be introduced as conservative or aggressive in the current model. Finally, the expansion of this study would be to include other relevant features and develop more advanced lane change detection models using Artificial Intelligence and Deep Learning for specific lane change types and extend the work to predict lane changes. doi:<https://doi.org/10.1016/j.aap.2020.105578>. <https://www.sciencedirect.com/science/article/pii/S0001457519315751>.

**Brad's Notes:** Interesting. Basic homework assignment.

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**Brad’s Notes:** Too Old

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Donmez, Birsan, Linda Ng Boyle, and John D. Lee. “Mitigating driver distraction with retrospective and concurrent feedback.” *Accident Analysis & Prevention* 40, no. 2 (2008): 776–786. doi:<https://doi.org/10.1016/j.aap.2007.09.023>. <https://www.sciencedirect.com/science/article/pii/S0001457507001698>.

**Brad’s Notes:** Too Old

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Du, Na, X. Jessie Yang, and Feng Zhou. “Psychophysiological responses to takeover requests in conditionally automated driving.” *Accident Analysis & Prevention* 148 (2020): 105804. doi:<https://doi.org/10.1016/j.aap.2020.105804>. <https://www.sciencedirect.com/science/article/pii/S0001457520316249>.

**Brad’s Notes:** Not our data.



Du, Na, Feng Zhou, Elizabeth M. Pulver, Dawn M. Tilbury, Lionel P. Robert, Anuj K. Pradhan, and X. Jessie Yang. “Predicting driver takeover performance in conditionally automated driving.” *Accident Analysis & Prevention* 148 (2020): 105748. doi:<https://doi.org/10.1016/j.aap.2020.105748>. <https://www.sciencedirect.com/science/article/pii/S0001457520315682>.

**Brad’s Notes:** Not our data.

Dunn, Naomi J., Thomas A. Dingus, Susan Soccolich, and William J. Horrey. “Investigating the impact of driving automation systems on distracted driving behaviors.” *Accident Analysis & Prevention* 156 (2021): 106152.

**Suggestions for Future Research:** While this study presents a relatively large-scale study of naturalistic driving data relative to driving automation use in comparison with other such studies, the sample size is not indicative of the U.S. population. Future studies should consider increasing the sample size. It should also be noted that driving automation system use was dependent upon the driver, not on an experimenter or other external prompt; thus, system use may have been dependent upon individual driver factors. Drivers in the VCC NDS had an app on their smart phone that provided safety-related driving information, such as weather, traffic, and driving conditions. The data reduction process did not (and could not) distinguish between study-related app use and personal phone use. Thus, the eye glance analyses focused on eyes-off-road glances rather than non-driving-related task glances. While NDSs allow the objective observation of driver performance and behavior, the nature of such studies precludes the use of intrusive instrumentation. As such, cognitive distraction could only be inferred from the study data and not directly measured. Refining the process of machine learning would be beneficial for future studies. For example, dash layout and automation icon appearance and location are vital to the machine-learning process; thus, vehicles with status icons that are not easy to distinguish were excluded from the current study. Finally, NDSs are dependent upon volunteer drivers. As such, a self-selection bias may exist.

doi:<https://doi.org/10.1016/j.aap.2021.106152>. <https://www.sciencedirect.com/science/article/pii/S0001457521001834>.

**Brad’s Notes:** Not our data. When do drivers engage their automated driving systems?

Eby, David W., Nina M. Silverstein, Lisa J. Molnar, David LeBlanc, and Geri Adler. “Driving behaviors in early stage dementia: A study using in-vehicle technology.” *PTW + Cognitive impairment and Driving Safety, Accident Analysis & Prevention* 49 (2012): 330–337. doi:<https://doi.org/10.1016/j.aap.2011.11.021>. <https://www.sciencedirect.com/science/article/pii/S0001457511003265>.

**Brad’s Notes:** Too Old

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Elhenawy, Mohammed, Arash Jahangiri, Hesham A. Rakha, and Ihab El-Shawarby. “Modeling driver stop/run behavior at the onset of a yellow indication considering driver run tendency and roadway surface conditions.” *Accident Analysis & Prevention* 83 (2015): 90–100. doi:<https://doi.org/10.1016/j.aap.2015.06.016>. <https://www.sciencedirect.com/science/article/pii/S0001457515300038>.

**Brad’s Notes:** Too Old

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Elmitiny, Noor, Xuedong Yan, Essam Radwan, Chris Russo, and Dina Nashar. “Classification analysis of driver’s stop/go decision and red-light running violation.” *Accident Analysis & Prevention* 42, no. 1 (2010): 101–111. doi:<https://doi.org/10.1016/j.aap.2009.07.007>. <https://www.sciencedirect.com/science/article/pii/S0001457509001729>.

**Brad’s Notes:** Too Old

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Essa, Mohamed, and Tarek Sayed. “Self-learning adaptive traffic signal control for real-time safety optimization.” *Accident Analysis & Prevention* 146 (2020): 105713. doi:<https://doi.org/10.1016/j.aap.2020.105713>. <https://www.sciencedirect.com/science/article/pii/S0001457520305388>.

Farid, Ahmed, Mohamed Abdel-Aty, and Jaeyoung Lee. “Comparative analysis of multiple techniques for developing and transferring safety performance functions.” *Accident Analysis & Prevention* 122 (2019): 85–98.

**Suggestions for Future Research:** Undoubtedly, this paper’s research is not without limitations. All SPFs, developed and transferred, suffer from omitted variable bias (Lord and Mannering, 2010) which results in errors associated with the estimates of the independent variables’ coefficients. Collecting data about more variables common to all the seven states is a challenge but worth the endeavor. Random parameters are also not taken into consideration. Mannering et al. (2016) assert that omitting random parameters inhibits the capturing of unobserved heterogeneity effects. However, incorporating random parameters renders the SPFs to be not transferable to other settings (Mannering et al., 2016). Incorporating finite mixture effects and random effects into the SPFs may also deter SPF transferability (Lord and Mannering, 2010). Furthermore, the generalized additive model and the hierarchical model structures are not attempted because they are also difficult to transfer to data of jurisdictions elsewhere (Lord and Mannering, 2010). Other than the regression techniques that are difficult to transfer, it should be noted that there are several viable techniques that could’ve been attempted. The transferability of Conway-Maxwell Poisson, gamma, negative multinomial, multivariate and generalized estimating equation SPFs (Lord and Mannering, 2010) is worth investigating. Another shortcoming is that the Tobit, RF, tree and hybrid models, recommended, are not applicable to before-and-after countermeasure deployment analysis using the empirical Bayes (EB) method prescribed by the HSM. The EB method depends on weights which are a function of the overdispersion of the NB model. Yet, Tobit, RF, tree and hybrid structures are applicable for evaluating the safety of alternative road designs.

doi:<https://doi.org/10.1016/j.aap.2018.09.024>. <https://www.sciencedirect.com/science/article/pii/S0001457518306754>.

**Brad’s Notes:** Interesting. Comparison of different models (ML and statistical) on different datasets from different states.

Favarò, Francesca, Sky Eurich, and Nazanin Nader. “Autonomous vehicles’ disengagements: Trends, triggers, and regulatory limitations.” *Accident Analysis & Prevention* 110 (2018): 136–148. doi:<https://doi.org/10.1016/j.aap.2017.11.001>. <https://www.sciencedirect.com/science/article/pii/S0001457517303822>.

**Brad’s Notes:** Too Old

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Filtiness, A.J., C.M. Rudin-Brown, C.M. Mulvihill, and M.G. Lenné. “Impairment of simulated motorcycle riding performance under low dose alcohol.” *Accident Analysis & Prevention* 50 (2013): 608–615. doi:<https://doi.org/10.1016/j.aap.2012.06.009>. <https://www.sciencedirect.com/science/article/pii/S0001457512002321>.

**Brad’s Notes:** Too Old

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Fischhoff, Baruch, Lita Furby, and Robin Gregory. “Evaluating voluntary risks of injury.” Special Issue Perspectives on Injury Prevention, *Accident Analysis & Prevention* 19, no. 1 (1987): 51–62. doi:[https://doi.org/10.1016/0001-4575\(87\)90017-0](https://doi.org/10.1016/0001-4575(87)90017-0). <https://www.sciencedirect.com/science/article/pii/0001457587900170>.

**Brad’s Notes:** Too Old

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Formosa, Nicolette, Mohammed Quddus, Stephen Ison, Mohamed Abdel-Aty, and Jinghui Yuan. “Predicting real-time traffic conflicts using deep learning.” *Accident Analysis & Prevention* 136 (2020): 105429.

**Suggestions for Future Research:** While the proposed DNN outperformed other machine learning classifiers, there are some limitations in the study such as the lack of detail in the data namely the weather conditions, drivers, road design which can improve the performance of the DNN. These added variables could be beneficial for the model to improve the prediction accuracy further since they can characterise a traffic condition. Moreover, in this work 50,000 data points were dealt with and by increasing the size of the data set the predictability of these models is expected to increase. Therefore, future work will include more testing especially in different weather conditions, to further assess the

performance of the model and tune it accordingly as well as testing the predictive performance of the DNN model on a validation model.  
doi:<https://doi.org/10.1016/j.aap.2019.105429>. <https://www.sciencedirect.com/science/article/pii/S000145751930973X>.

**Brad's Notes:** Interesting, but not our data.  
Only talks about accuracy in the abstract, introduction, and conclusion, although does talk about  
Prediction models for one roadway can't be applied to others. (lots of studies, but not cited).

Interestingly, gives Sensitivity, False Alarm Rate (FAR) and Precision as percentages, but Accuracy as a decimal.

Fung, Ivan W.H., Tommy Y. Lo, and Karen C.F. Tung. "Towards a better reliability of risk assessment: Development of a qualitative & quantitative risk evaluation model (Q2REM) for different trades of construction works in Hong Kong." *Intelligent Speed Adaptation + Construction Projects, Accident Analysis & Prevention* 48 (2012): 167–184. doi:<https://doi.org/10.1016/j.aap.2011.05.011>. <https://www.sciencedirect.com/science/article/pii/S0001457511001308>.

**Brad's Notes:** Too Old

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Furlan, Andrea D., Tara Kajaks, Margaret Tiong, Martin Lavallière, Jennifer L. Campos, Jessica Babineau, Shabnam Haghzare, Tracey Ma, and Brenda Vrkljan. "Advanced vehicle technologies and road safety: A scoping review of the evidence." *Accident Analysis & Prevention* 147 (2020): 105741. doi:<https://doi.org/10.1016/j.aap.2020.105741>. <https://www.sciencedirect.com/science/article/pii/S000145752031561X>.

**Brad's Notes:** Not ML

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Giummarra, Melita J., Georgina Lau, Genevieve Grant, and Belinda J. Gabbe. "A systematic review of the association between fault or blame-related attributions and procedures after transport injury and health and work-related outcomes." *Accident Analysis & Prevention* 135 (2020): 105333.

**Suggestions for Future Research:** None  
, doi:<https://doi.org/10.1016/j.aap.2019.105333>. <https://www.sciencedirect.com/science/article/pii/S0001457519303781>.

**Brad's Notes:** Interesting for Text Mining

Goh, Yang Miang, and C.U. Ubeynarayana. "Construction accident narrative classification: An evaluation of text mining techniques." *Accident Analysis & Prevention* 108 (2017): 122–130. doi:<https://doi.org/10.1016/j.aap.2017.08.026>. <https://www.sciencedirect.com/science/article/pii/S0001457517303068>.

**Brad's Notes:** Too Old

Goh, Yang Miang, Chalani U. Ubeynarayana, Karen Le Xin Wong, and Brian H.W. Guo. "Factors influencing unsafe behaviors: A supervised learning approach." *Accident Analysis & Prevention* 118 (2018): 77–85. doi:<https://doi.org/10.1016/j.aap.2018.06.002>. <https://www.sciencedirect.com/science/article/pii/S0001457518302173>.

**Brad's Notes:** Too Old

Gold, Christian, Riender Happee, and Klaus Bengler. "Modeling take-over performance in level 3 conditionally automated vehicles." *Simulation of Traffic Safety in the Era of Advances in Technologies, Accident Analysis & Prevention* 116 (2018): 3–13. doi:<https://doi.org/10.1016/j.aap.2017.11.009>. <https://www.sciencedirect.com/science/article/pii/S0001457517303962>.

**Brad's Notes:** Too Old

Goncalves, Rafael C., Tyron L. Louw, Manuela Quaresma, Ruth Madigan, and Natasha Merat. “The effect of motor control requirements on drivers’ eye-gaze pattern during automated driving.” *Accident Analysis & Prevention* 148 (2020): 105788. doi:<https://doi.org/10.1016/j.aap.2020.105788>. <https://www.sciencedirect.com/science/article/pii/S0001457520316080>.

Gong, Yaobang, Mohamed Abdel-Aty, Jinghui Yuan, and Qing Cai. “Multi-Objective reinforcement learning approach for improving safety at intersections with adaptive traffic signal control.” *Accident Analysis & Prevention* 144 (2020): 105655.

**Suggestions for Future Research:** Admittedly, there are several limitations. As the weighted sum approach is not guaranteed to be Pareto-optimal, the study could be improved by calculating the Pareto-front using more computationally efficient algorithms. Meanwhile, other kinds of safety measures such as traffic conflicts could be tested as the safety objective using the proposed algorithm. Moreover, as vehicles’ operation speeds are correlated with both efficiency and safety, controlling vehicles’ speed directly may provide additional safety and operational benefits (Li et al., 2018; Ma et al., 2017; Qu et al., 2020; Zhou et al., 2020). With the rapid development of the connected and automated vehicles (CAV), a safety-oriented control system that jointly controls of traffic signals and CAV would be a valuable future research direction. doi:<https://doi.org/10.1016/j.aap.2020.105655>. <https://www.sciencedirect.com/science/article/pii/S0001457520303948>.

**Brad’s Notes:** Multi-Objective Deep Reinforcement Learning. Adaptive traffic signal control. Not our data. Interesting for Dr. Jin?

Grahn, Hilkka, Tuomo Kujala, Johanna Silvennoinen, Aino Leppänen, and Pertti Saariluoma. “Expert Drivers’ Prospective Thinking-Aloud to Enhance Automated Driving Technologies – Investigating Uncertainty and Anticipation in Traffic.” *Accident Analysis & Prevention* 146 (2020): 105717. doi:<https://doi.org/10.1016/j.aap.2020.105717>. <https://www.sciencedirect.com/science/article/pii/S0001457520306746>.

**Brad's Notes:** Not ML, Not our data.

Gregersen, Nils Petter, and Per Bjurulf. "Young novice drivers: Towards a model of their accident involvement." *Accident Analysis & Prevention* 28, no. 2 (1996): 229–241. doi:[https://doi.org/10.1016/0001-4575\(95\)00063-1](https://doi.org/10.1016/0001-4575(95)00063-1). <https://www.sciencedirect.com/science/article/pii/0001457595000631>.

**Brad's Notes:** Too Old

Gstalter, Herbert, and Wolfgang Fastenmeier. "Reliability of drivers in urban intersections." *Accident Analysis & Prevention* 42, no. 1 (2010): 225–234. doi:<https://doi.org/10.1016/j.aap.2009.07.021>. <https://www.sciencedirect.com/science/article/pii/S0001457509002061>.

**Brad's Notes:** Too Old

Guastello, Stephen J. "Catastrophe modeling of the accident process: Evaluation of an accident reduction program using the Occupational Hazards Survey." *Accident Analysis & Prevention* 21, no. 1 (1989): 61–77. doi:[https://doi.org/10.1016/0001-4575\(89\)90049-3](https://doi.org/10.1016/0001-4575(89)90049-3). <https://www.sciencedirect.com/science/article/pii/0001457589900493>.

**Brad's Notes:** Too Old

Gulino, Michelangelo-Santo, Leonardo Di Gangi, Alessio Sortino, and Dario Vangi. "Injury risk assessment based on pre-crash variables: The role of closing velocity and impact eccentricity." *Accident Analysis & Prevention* 150 (2021): 105864.



**Suggestions for Future Research:** Notwithstanding the interesting highlights obtained, it is worth evidencing that the analysis is focused on the determination of IR by the MAIS 3+ index (serious injuries). The soundness of the results in terms of Vr and CMI influence on the injury outcome can be extended by studies focused on: • a higher number of injury degrees (different MAIS); • different injury severity indexes (e.g., ISS); • an injury index which refers to single body segments (AIS). This would additionally allow for a broader-spectrum study, employing the models classified as most promising by the performed analysis. The IR models which have been derived are valid for all collision types, because the value of Vr and CMI is based on a posteriori data (by  $\Delta V$  value and Eq. (3)); conversely, calculation of  $\Delta V$  by Eq. (2) may be inappropriate if sliding occurs during the collision. However, in this latter case, only a limited part of Vr is converted into  $\Delta V$  (low Vr-PDOF): a low IR value associated with the collision is obtained and, as a consequence, a lower relevance of sliding impacts in a priori analyses can be highlighted if compared to full impacts. It must be mentioned that the check applied to increase the quality of the analysis (Eq. (6)) exerts a significant effect on the remaining number of cases to be processed; however, this check can be modified or excluded to include a higher number of accidents: even if more cases can improve the fitting quality in practice, the use of partially incorrect data can significantly affect the quality of the resulting model (Vangi et al., 2019a). For what specifically concerns the derived models, it is worth noting that they are obtained using American data only; given the differences between distinct countries in terms of both data collection (in procedure and accuracy (Fildes et al., 2013)) and crashworthiness of vehicles (Flanagan et al., 2018), the proposed IR models need to be modified and contextualized based on the specific scope. The type-approval year of the vehicle model also affects the passive safety datum: the registration year is considered as an indicator of the vehicle generation (and crashworthiness) in the derived IR models because it is the sole element available from the NASS/CDS database; considering the type-approval year, rather than the registration year, could be beneficial to enhance the overall fitting quality.

doi:<https://doi.org/10.1016/j.aap.2020.105864>. <https://www.sciencedirect.com/science/article/pii/S0001457520316845>.

**Brad's Notes:** Not our data. Interesting for thorough analysis.

Guo, Xiaoyu, Lingtao Wu, and Dominique Lord. "Generalized criteria for evaluating hotspot identification methods." *Accident Analysis & Prevention* 145 (2020): 105684. doi:<https://doi.org/10.1016/j.aap.2020.105684>. <https://www.sciencedirect.com/science/article/pii/S0001457520303511>.

**Brad's Notes:** Not ML

Guo, Yanyong, Zhibin Li, Pan Liu, and Yao Wu. "Modeling correlation and heterogeneity in crash rates by collision types using full bayesian random parameters multivariate Tobit model." *Accident Analysis & Prevention* 128 (2019): 164–174.

**Suggestions for Future Research:** The analysis suggests the considerable potential of the proposed model in crash rates analysis at freeway diverge areas. Although some findings regarding collision types were obtained, there are some limitations to this study. First, research efforts still need to be conducted with crash data collected from other states or areas to validate the results of this paper before the results can be used to direct the exit ramp designs. Second, this study did not give enough insight into occurrence mechanism for different crashes. Rear-end crashes could be related to abrupt deceleration at diverge bottlenecks, and sideswipe/angle crashes could be caused by intense lane changes. As such, high-resolution traffic data from loop detectors on freeway mainlines and ramps could be collected to develop the real time crash risk prediction models in future study. Third, the insignificant variables that excluded in the final models can introduce omitted variable bias, which should be considered by optimizing the statistical modeling frameworks. There are several areas of further research that can be investigated to improve the current study. First, due to the limited access to the crash severity, this paper did not incorporate injury-severity in the developed models. An extension of the current study can examine the injury-severity rates across collision types. This will provide new insights regarding the injury-severity mechanism across different collision types. Second, this study did not consider the temporal and spatial correlation in crash rates, further study could be

conducted to extend the current model to accommodate the temporal and spatial effect. Moreover, further research efforts could also be made to compare the risk factors with crash frequency and that with crash rates. Last but not least, future study can further decompose the Tobit coefficients to the effect of the parameters on the overall rates, and on the probability of an observation being in the zero-state. They will help with the model parameters' inferences.

doi:<https://doi.org/10.1016/j.aap.2019.04.013>. <https://www.sciencedirect.com/science/article/pii/S0001457518311576>.

**Brad's Notes:** Data from 367 freeway exits. Not ML

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Gupta, Surabhi, Maria Vasardani, Bharat Lohani, and Stephan Winter. "Pedestrian's risk-based negotiation model for self-driving vehicles to get the right of way." *Accident Analysis & Prevention* 124 (2019): 163–173. doi:<https://doi.org/10.1016/j.aap.2019.01.003>. <https://www.sciencedirect.com/science/article/pii/S0001457518308716>.

**Brad's Notes:** Not our data. Not ML. Model for how autonomous vehicles

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Haghani, Milad, Michiel C.J. Bliemer, Bilal Farooq, Inhi Kim, Zhibin Li, Cheol Oh, Zahra Shahhoseini, and Hamish MacDougall. "Applications of brain imaging methods in driving behaviour research." *Accident Analysis & Prevention* 154 (2021): 106093. doi:<https://doi.org/10.1016/j.aap.2021.106093>. <https://www.sciencedirect.com/science/article/pii/S000145752100124X>.

**Brad's Notes:** Not ML

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Hakim, Simon, Daniel Shefer, A.S. Hakkert, and Irit Hocherman. "A critical review of macro models for road accidents." Special Issue: Theoretical models for traffic safety, *Accident Analysis & Prevention* 23, no. 5 (1991): 379–400. doi:[https://doi.org/10.1016/0001-4575\(91\)90058-D](https://doi.org/10.1016/0001-4575(91)90058-D). <https://www.sciencedirect.com/science/article/pii/S000145759190058D>.

**Brad's Notes: Too Old**

Halbersberg, Dan, and Boaz Lerner. "Young driver fatal motorcycle accident analysis by jointly maximizing accuracy and information." *Accident Analysis & Prevention* 129 (2019): 350–361. doi:<https://doi.org/10.1016/j.aap.2019.04.016>. <https://www.sciencedirect.com/science/article/pii/S0001457518304561>.

Haleem, Kirolos, Priyanka Alluri, and Albert Gan. "Analyzing pedestrian crash injury severity at signalized and non-signalized locations." *Accident Analysis & Prevention* 81 (2015): 14–23. doi:<https://doi.org/10.1016/j.aap.2015.04.025>. <https://www.sciencedirect.com/science/article/pii/S0001457515001621>.

**Brad's Notes: Too Old**

Hall, Thomas, and Andrew P. Tarko. "Adequacy of negative binomial models for managing safety on rural local roads." *Accident Analysis & Prevention* 128 (2019): 148–158.

**Suggestions for Future Research:** Future research should compare safety effects estimated on rural local roads with those effects on well-studied rural arterial roads. If the similarity of effects on both road types are confirmed, then this could allow transferring at least part of the knowledge of highway safety factors (for example, crash modification factors) to rural local roads to facilitate the development of road screening and safety improvement measures for these roads. While the current study focused on rural local intersections, future research should extend further to cover rural local segments. A similar statistical methodology may be used in examining the effect of segmentlevel variables related to the road curvature, driveways and access points, and the presence of roadside obstructions, among other factors. Segments may also offer further opportunities for safety improvements through the alignment, cross-sectional, and roadside components.

doi:<https://doi.org/10.1016/j.aap.2019.03.001>. <https://www.sciencedirect.com/science/article/pii/S0001457518306808>.

**Brad's Notes: Not ML**

Hancock, P.A., M. Lesch, and L. Simmons. "The distraction effects of phone use during a crucial driving maneuver." *Accident Analysis & Prevention* 35, no. 4 (2003): 501–514. doi:[https://doi.org/10.1016/S0001-4575\(02\)00028-3](https://doi.org/10.1016/S0001-4575(02)00028-3). <https://www.sciencedirect.com/science/article/pii/S0001457502000283>.

**Brad's Notes:** Too Old

Hancock, P.A., and W.B. Verwey. "Fatigue, workload and adaptive driver systems." *Fatigue and Transport, Accident Analysis & Prevention* 29, no. 4 (1997): 495–506. doi:[https://doi.org/10.1016/S0001-4575\(97\)00029-8](https://doi.org/10.1016/S0001-4575(97)00029-8). <https://www.sciencedirect.com/science/article/pii/S0001457597000298>.

**Brad's Notes:** Too Old

Hänninen, Maria. "Bayesian networks for maritime traffic accident prevention: Benefits and challenges." *Accident Analysis & Prevention* 73 (2014): 305–312. doi:<https://doi.org/10.1016/j.aap.2014.09.017>. <https://www.sciencedirect.com/science/article/pii/S0001457514002735>.

**Brad's Notes:** Too Old

Harb, Rami, Xuedong Yan, Essam Radwan, and Xiaogang Su. "Exploring precrash maneuvers using classification trees and random forests." *Accident Analysis & Prevention* 41, no. 1 (2009): 98–107. doi:<https://doi.org/10.1016/j.aap.2008.09.009>. <https://www.sciencedirect.com/science/article/pii/S0001457508001887>.

**Brad's Notes:** Too Old

Harrison, Warren A., and Ron Christie. "Exposure survey of motorcyclists in New South Wales." *Accident Analysis & Prevention* 37, no. 3 (2005): 441–451. doi:<https://doi.org/10.1016/j.aap.2004.12.005>. <https://www.sciencedirect.com/science/article/pii/S0001457504001216>.

**Brad's Notes:** Too Old

Hauer, Ezra. "An application of the likelihood/bayes approach to the estimation of safety countermeasure effectiveness." *Accident Analysis & Prevention* 15, no. 4 (1983): 287–298. doi:[https://doi.org/10.1016/0001-4575\(83\)90053-2](https://doi.org/10.1016/0001-4575(83)90053-2). <https://www.sciencedirect.com/science/article/pii/0001457583900532>.

**Brad's Notes:** Too Old

———. "Reflections on methods of statistical inference in research on the effect of safety countermeasures." *Accident Analysis & Prevention* 15, no. 4 (1983): 275–285. doi:[https://doi.org/10.1016/0001-4575\(83\)90052-0](https://doi.org/10.1016/0001-4575(83)90052-0). <https://www.sciencedirect.com/science/article/pii/0001457583900520>.

**Brad's Notes:** Too Old

Hedlund, James, Robert Arnold, Ezio Cerrelli, Susan Partyka, Paul Hoxie, and David Skinner. "An assessment of the 1982 traffic fatality decrease." *Accident Analysis & Prevention* 16, no. 4 (1984): 247–261. doi:[https://doi.org/10.1016/0001-4575\(84\)90020-4](https://doi.org/10.1016/0001-4575(84)90020-4). <https://www.sciencedirect.com/science/article/pii/0001457584900204>.

**Brad's Notes:** Too Old

Hong, Jungyeol, Reuben Tamakloe, and Dongjoo Park. "Application of association rules mining algorithm for hazardous materials transportation crashes on expressway." *Accident Analysis & Prevention* 142 (2020): 105497. doi:<https://doi.org/10.1016/j.aap.2020.105497>. <https://www.sciencedirect.com/science/article/pii/S0001457519314587>.

**Brad's Notes:** Interesting?

Hong, Zihan, Ying Chen, and Yang Wu. “A driver behavior assessment and recommendation system for connected vehicles to produce safer driving environments through a “follow the leader” approach.” *Accident Analysis & Prevention* 139 (2020): 105460.

**Suggestions for Future Research:** Finally, several extensions of this work are proposed. First, different levels of connectivity for longer tests with more vehicles within other networks, especially in rural areas, would be worthwhile. Second, the data library could be improved by introducing more trajectory data in addition to other types of data describing the driving situations, particularly weather, road conditions, and the driving culture (i.e. social norms) in the area/city/country where the driving data is collected. Third, the proposed system is extendable to an on-line case which can be updated in real-time. Fourth, as stated in Section 5.2, the importance of compliance rate could be further explored with a set of more systematically designed experiments. With additional training data and more robust simulations, the attractiveness of this system for deploying a wider range of traffic management interventions and individual driver guidance is indeed possible.

doi:<https://doi.org/10.1016/j.aap.2020.105460>. <https://www.sciencedirect.com/science/article/pii/S0001457519307377>.

**Brad’s Notes:** Not ML

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Hossain, Moinul, Mohamed Abdel-Aty, Mohammed A. Quddus, Yasunori Muromachi, and Soumik Nafis Sadeek. “Real-time crash prediction models: State-of-the-art, design pathways and ubiquitous requirements.” *Accident Analysis & Prevention* 124 (2019): 66–84. doi:<https://doi.org/10.1016/j.aap.2018.12.022>. <https://www.sciencedirect.com/science/article/pii/S000145751831217X>.

**Brad’s Notes:** Interesting. Review of previous papers with text mining.

Hossain, Moinul, and Yasunori Muromachi. “Understanding crash mechanism on urban expressways using high-resolution traffic data.” *Accident Analysis & Prevention* 57 (2013): 17–29. doi:<https://doi.org/10.1016/j.aap.2013.03.024>. <https://www.sciencedirect.com/science/article/pii/S000145751300122X>.

**Brad’s Notes:** Too Old

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Hu, Jiajie, Ming-Chun Huang, and Xiong Yu. “Efficient mapping of crash risk at intersections with connected vehicle data and deep learning models.” *Accident Analysis & Prevention* 144 (2020): 105665. doi:<https://doi.org/10.1016/j.aap.2020.105665>. <https://www.sciencedirect.com/science/article/pii/S0001457519319062>.

**Brad’s Notes:** Not our data. Connected vehicle data. Interesting for clear description of method.

Huang, Tingting, Shuo Wang, and Anuj Sharma. “Highway crash detection and risk estimation using deep learning.” *Accident Analysis & Prevention* 135 (2020): 105392. doi:<https://doi.org/10.1016/j.aap.2019.105392>. <https://www.sciencedirect.com/science/article/pii/S000145751930555X>.

**Brad’s Notes:** Not our data. Radar sensors

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Huang, Yueng-hsiang, Yimin He, Jin Lee, and Changya Hu. “Key drivers of trucking safety climate from the perspective of leader-member exchange: Bayesian network predictive modeling approach.” *Accident Analysis & Prevention* 150 (2021): 105850. doi:<https://doi.org/10.1016/j.aap.2020.105850>. <https://www.sciencedirect.com/science/article/pii/S0001457520316705>.

**Brad’s Notes:** Not our data, Not ML. Truckers’ Opinions of Safety.



Hunn, Bruce P., and Thomas A. Dingus. “Interactivity, information, and compliance cost in a consumer product warning scenario.” *Accident Analysis & Prevention* 24, no. 5 (1992): 497–505. doi:[https://doi.org/10.1016/0001-4575\(92\)90058-Q](https://doi.org/10.1016/0001-4575(92)90058-Q). <https://www.sciencedirect.com/science/article/pii/000145759290058Q>.

**Brad’s Notes:** Too Old

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Hyun, Kyung (Kate), Suman Kumar Mitra, Kyungsoo Jeong, and Andre Tok. “Understanding the effects of vehicle platoons on crash type and severity.” *Accident Analysis & Prevention* 149 (2021): 105858. doi:<https://doi.org/10.1016/j.aap.2020.105858>. <https://www.sciencedirect.com/science/article/pii/S000145752031678X>.

Ijaz, Muhammad, Liu lan, Muhammad Zahid, and Arshad Jamal. “A comparative study of machine learning classifiers for injury severity prediction of crashes involving three-wheeled motorized rickshaw.” *Accident Analysis & Prevention* 154 (2021): 106094. doi:<https://doi.org/10.1016/j.aap.2021.106094>. <https://www.sciencedirect.com/science/article/pii/S0001457521001251>.

Iranitalab, Amirfarrokh, and Aemal Khattak. “Comparison of four statistical and machine learning methods for crash severity prediction.” *Accident Analysis & Prevention* 108 (2017): 27–36. doi:<https://doi.org/10.1016/j.aap.2017.08.008>. <https://www.sciencedirect.com/science/article/pii/S0001457517302865>.

**Brad’s Notes:** Too Old

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Islam, Zubayer, Mohamed Abdel-Aty, Qing Cai, and Jinghui Yuan. “Crash data augmentation using variational autoencoder.” *Accident Analysis & Prevention* 151 (2021): 105950.

**Suggestions for Future Research:** Future studies can train crash prediction models on more complex and non-linear algorithms that do not perform well on small datasets. Using VAE as a data generation tool in the pipeline would definitely aid in generating substantial data to train on non-linear models. Furthermore, there could be more work relating VAE that could have one more class in between crash and non-crash: crash-prone. The training data of this region could be derived from the false positives from our VAE model.

doi:<https://doi.org/10.1016/j.aap.2020.105950>. <https://www.sciencedirect.com/science/article/pii/S000145752031770X>.

**Brad's Notes:** Interesting. Data augmentation.

Jacobé de Naurois, Charlotte, Christophe Bourdin, Clément Bougard, and Jean-Louis Vercher. “Adapting artificial neural networks to a specific driver enhances detection and prediction of drowsiness.” *Accident Analysis & Prevention* 121 (2018): 118–128. doi:<https://doi.org/10.1016/j.aap.2018.08.017>. <https://www.sciencedirect.com/science/article/pii/S0001457518304743>.

**Brad's Notes:** Too Old

Jacobé de Naurois, Charlotte, Christophe Bourdin, Anca Stratulat, Emmanuelle Diaz, and Jean-Louis Vercher. “Detection and prediction of driver drowsiness using artificial neural network models.” 10th International Conference on Managing Fatigue: Managing Fatigue to Improve Safety, Wellness, and Effectiveness”. *Accident Analysis & Prevention* 126 (2019): 95–104. doi:<https://doi.org/10.1016/j.aap.2017.11.038>. <https://www.sciencedirect.com/science/article/pii/S0001457517304347>.

**Brad's Notes:** Not our data. Driving simulator.

Jahangiri, Arash, Hesham Rakha, and Thomas A. Dingus. “Red-light running violation prediction using observational and simulator data.” *Accident Analysis & Prevention* 96 (2016): 316–328. doi:<https://doi.org/10.1016/j.aap.2016.06.009>. <https://www.sciencedirect.com/science/article/pii/S0001457516302056>.

**Brad's Notes: Too Old**

Jazayeri, Ali, John Ray B. Martinez, Helen S. Loeb, and Christopher C. Yang. "The Impact of driver distraction and secondary tasks with and without other co-occurring driving behaviors on the level of road traffic crashes." *Accident Analysis & Prevention* 153 (2021): 106010. doi:<https://doi.org/10.1016/j.aap.2021.106010>. <https://www.sciencedirect.com/science/article/pii/S0001457521000415>.

Jeong, Heejin, Youngchan Jang, Patrick J. Bowman, and Neda Masoud. "Classification of motor vehicle crash injury severity: A hybrid approach for imbalanced data." *Accident Analysis & Prevention* 120 (2018): 250–261. doi:<https://doi.org/10.1016/j.aap.2018.08.025>. <https://www.sciencedirect.com/science/article/pii/S0001457518305232>.

**Brad's Notes: Too Old**

Jetto, Kamal, Zineb Tahiri, Abdelilah Benyoussef, and Abdallah El Kenz. "Cognitive anticipation cellular automata model: An attempt to understand the relation between the traffic states and rear-end collisions." *Accident Analysis & Prevention* 142 (2020): 105507. doi:<https://doi.org/10.1016/j.aap.2020.105507>. <https://www.sciencedirect.com/science/article/pii/S0001457519316859>.

**Brad's Notes: Not ML, Not our data**

Jha, Alok Nikhil, Niladri Chatterjee, and Geetam Tiwari. "A performance analysis of prediction techniques for impacting vehicles in hit-and-run road accidents." *Accident Analysis & Prevention* 157 (2021): 106164.

**Suggestions for Future Research:** The work can be extended by applying other classification and regression models, such as self-organizing maps, random forest, neural networks, clustering techniques, rough sets and deep learning techniques.

doi:<https://doi.org/10.1016/j.aap.2021.106164>. <https://www.sciencedirect.com/science/article/pii/S0001457521001950>.

**Brad’s Notes:** Nothing new. We did a thing.

Ji, Ang, and David Levinson. “An energy loss-based vehicular injury severity model.” *Accident Analysis & Prevention* 146 (2020): 105730.

**Suggestions for Future Research:** Future research could extend the model by studying more crashes with different collision angles and establishing the relationships between crash types and their respective  $\alpha$  values. It may also depend on whether fragile or weak structures of vehicles receive the crash impact. Other factors that significantly influence the energy absorption by vehicles are also expected to improve estimation outcomes. Extensions to consider elastic collisions and restitution coefficients may provide additional useful insights for realistic crash studies.

doi:<https://doi.org/10.1016/j.aap.2020.105730>. <https://www.sciencedirect.com/science/article/pii/S0001457519315519>.

**Brad’s Notes:** Predicting injury based on relative masses of vehicles.

Jiang, Feifeng, Kwok Kit Richard Yuen, and Eric Wai Ming Lee. “A long short-term memory-based framework for crash detection on freeways with traffic data of different temporal resolutions.” *Accident Analysis & Prevention* 141 (2020): 105520.

**Suggestions for Future Research:** The limitation of this study is that cases with very poor data quality (e.g., no data recorded in more than one stations) are deleted in data preprocessing. However, this kind of missing data accounts for a large proportion of all cases. Future work needs to propose proper methods to supplement these missing data and improve prediction performance.

doi:<https://doi.org/10.1016/j.aap.2020.105520>. <https://www.sciencedirect.com/science/article/pii/S0001457519317713>.

**Brad’s Notes:** Interesting for taking temporal resolution into account. Real-time applications?

Jin, Mengxia, Guangquan Lu, Facheng Chen, Xi Shi, Haitian Tan, and Junda Zhai. “Modeling takeover behavior in level 3 automated driving via a structural equation model: Considering the mediating role of trust.” *Accident Analysis & Prevention* 157 (2021): 106156. doi:<https://doi.org/10.1016/j.aap.2021.106156>. <https://www.sciencedirect.com/science/article/pii/S0001457521001871>.

**Brad’s Notes:** Not our data. Not ML

John C., Ferguson, McNally Michael S., and Booth Richard F. “Individual characteristics as predictors of accidental injuries in naval personnel.” *Accident Analysis & Prevention* 16, no. 1 (1984): 55–62. doi:[https://doi.org/10.1016/0001-4575\(84\)90006-X](https://doi.org/10.1016/0001-4575(84)90006-X). <https://www.sciencedirect.com/science/article/pii/000145758490006X>.

**Brad’s Notes:** Too Old

Kao, Henry S.R. “Feedback concepts of driver behavior and the highway information system.” *Accident Analysis & Prevention* 1, no. 1 (1969): 65–76. doi:[https://doi.org/10.1016/0001-4575\(69\)90005-0](https://doi.org/10.1016/0001-4575(69)90005-0). <https://www.sciencedirect.com/science/article/pii/0001457569900050>.

**Brad’s Notes:** Too Old

Katanalp, Burak Yiğit, and Ezgi Eren. “The novel approaches to classify cyclist accident injury-severity: Hybrid fuzzy decision mechanisms.” *Accident Analysis & Prevention* 144 (2020): 105590. doi:<https://doi.org/10.1016/j.aap.2020.105590>. <https://www.sciencedirect.com/science/article/pii/S0001457520305522>.

Katrakazas, Christos, Mohammed Quddus, and Wen-Hua Chen. “A new integrated collision risk assessment methodology for autonomous vehicles.” *Accident Analysis & Prevention* 127 (2019): 61–79.

**Suggestions for Future Research:** None

, doi:<https://doi.org/10.1016/j.aap.2019.01.029>. <https://www.sciencedirect.com/science/article/pii/S0001457518306614>.

**Brad's Notes:** Perhaps Interesting. I think they combined two types of data in the analysis.

Katrakazas, Christos, Athanasios Theofilatos, Md Ashraful Islam, Eleonora Papadimitriou, Loukas Dimitriou, and Constantinos Antoniou. "Prediction of rear-end conflict frequency using multiple-location traffic parameters." *Accident Analysis & Prevention* 152 (2021): 106007. doi:<https://doi.org/10.1016/j.aap.2021.106007>. <https://www.sciencedirect.com/science/article/pii/S0001457521000385>.

**Brad's Notes:** Not ML

Keramati, Amin, Pan Lu, Amirfarrokh Iranitalab, Danguang Pan, and Ying Huang. "A crash severity analysis at highway-rail grade crossings: The random survival forest method." *Accident Analysis & Prevention* 144 (2020): 105683.

**Suggestions for Future Research:** None  
, doi:<https://doi.org/10.1016/j.aap.2020.105683>. <https://www.sciencedirect.com/science/article/pii/S0001457519317749>.

**Brad's Notes:** Highway-Rail Grade Crossing, found two correlated countermeasures, with temporal effects.

Khan, Md Nasim, and Mohamed M. Ahmed. "Trajectory-level fog detection based on in-vehicle video camera with TensorFlow deep learning utilizing SHRP2 naturalistic driving data." *Accident Analysis & Prevention* 142 (2020): 105521. doi:<https://doi.org/10.1016/j.aap.2020.105521>. <https://www.sciencedirect.com/science/article/pii/S0001457519316422>.

Khan, Shah Khalid, Nirajan Shiwakoti, Peter Stasinopoulos, and Yilun Chen. "Cyber-attacks in the next-generation cars, mitigation techniques, anticipated readiness and future directions." *Accident Analysis & Prevention* 148 (2020): 105837. doi:<https://doi.org/10.1016/j.aap.2020.105837>. <https://www.sciencedirect.com/science/article/pii/S0001457520316572>.

**Brad's Notes:** Not ML

Khattak, Zulqarnain H., and Michael D. Fontaine. "A Bayesian modeling framework for crash severity effects of active traffic management systems." *Accident Analysis & Prevention* 145 (2020): 105544.

**Suggestions for Future Research:** There are several avenues for future research. The crash severity results from this study can be compared with individual models representing frequency of crashes and crash types. The insights about the effects of ATM systems on crash severities can be enhanced with data from additional deployments across different states. ATM systems are unique and these deployments are rare across the country, with limited high-quality data, which makes the current study one of the first to analyze the severity impact of ATM systems. The current study will serve as a base for future studies to draw a comparison against performance of ATM systems as more data becomes available. **Further, a comparison between econometric models and machine learning algorithms can be conducted and used to estimate models with high prediction accuracy.** Finally, the ATMs impact on freeway crash severities was examined in this research. However, future research could focus on examining similar severity impacts on freeway interchange influence areas. The speed of vehicles involved in a crash is an important factor that could influence the crash severity. However, the only speed estimates available are those provided on the police report, which are either estimated by the drivers involved or the responding officer after the crash. Given the potential inaccuracies in this data, speed estimates were not used. Future studies could collect these real-time at-fault speeds (Khattak et al., 2018a) using connected vehicle data, which could provide useful insights into the impact of this variable on crash severity prior to involvement in a crash event.

doi:<https://doi.org/10.1016/j.aap.2020.105544>. <https://www.sciencedirect.com/science/article/pii/S0001457519317762>.

**Brad's Notes:** Not ML, but interesting for recommending a comparison between econometric models and ML algorithms.

Khattak, Zulqarnain H., Michael D. Fontaine, Wan Li, Asad J. Khattak, and Thomas Karnowski. “Investigating the relation between instantaneous driving decisions and safety critical events in naturalistic driving environment.” *Accident Analysis & Prevention* 156 (2021): 106086. doi:<https://doi.org/10.1016/j.aap.2021.106086>. <https://www.sciencedirect.com/science/article/pii/S0001457521001172>.

#### **Brad’s Notes:** Not ML

Khattak, Zulqarnain H., Michael D. Fontaine, Brian L. Smith, and Jiaqi Ma. “Crash severity effects of adaptive signal control technology: An empirical assessment with insights from Pennsylvania and Virginia.” *Accident Analysis & Prevention* 124 (2019): 151–162.

**Suggestions for Future Research:** Furthermore, the use of random parameter logit model with heterogeneity in means and variance may help in improving the prediction power of the severe plus moderate injury category at the cost of neglecting the ordinal nature of severities. It may also make sense to try machine learning algorithms such (K-Nearest Neighbor Classifier and Random Forest) instead of discrete choice models, which could yield better prediction power for disaggregate severity levels since they don’t rely on making assumptions about the functional form of the data and require fewer parameters to tune. Since the main objective of this paper was to perform exploratory analysis of ASCT’s impact on signalized intersection crash severity, crash frequency and individual crash type models were not considered in this research. Another reason was that the authors have already developed crash modification factors for ASCT (Khattak et al., 2017a) and considered those to be more useful to both practitioners and researchers. However, an interesting future research direction would be to examine how the results of crash frequency and individual crash type models compare with the crash severities presented in this paper and the CMFs developed by the authors. The optimization algorithms vary across the ASCT systems and may provide differing benefits thus, future studies could also look at crash severity effects of other ASCT systems as opposed to the two systems analyzed in this research and draw a comparison. Likewise, the emergence of automated traffic signal performance measurement systems provides an additional technology that could be compared against ASCT. With the development of connected



and automated vehicles (CAV), CAV-enabled signal controls may also be analyzed in the future to see whether they provide any additional safety benefits compared to the ASCT systems analyzed in this research. Since crash trends vary across states, data from additional states across the United States can also provide significant insights about the crash severity effects of ASCTs. Another promising research direction could be to analyze the different econometric models and machine learning algorithms in order to see which modeling approach could provide better prediction accuracy with the severe plus moderate injury category, since that category had the lowest number of observations.

doi:<https://doi.org/10.1016/j.aap.2019.01.008>. <https://www.sciencedirect.com/science/article/pii/S0001457519300399>.

#### **Brad's Notes:** Not ML

Kidando, Emmanuel, Angela E. Kitali, Boniphace Kutela, Mahyar Ghorbanzadeh, Aican Karaer, Mohammadreza Koloushani, Ren Moses, Eren E. Ozguven, and Thobias Sando. "Prediction of vehicle occupants injury at signalized intersections using real-time traffic and signal data." *Accident Analysis & Prevention* 149 (2021): 105869.

**Suggestions for Future Research:** It is important to note that though this study substantiated the influence of real-time data on the severity of occupants involved in signalized intersection crashes, there are some limitations. It is well established that the approaching speed of vehicles involved in a crash plays a significant role in the outcome of the occupant injury. However, it was not possible to derive this parameter from the detector data. Thus, future research can investigate the role of approaching real-time speed together with other risk factors on the occupant injury. It will be an opportunity for future work to investigate the impact of time intervals such as 2, 5, and 15 min in the real-time safety analysis. Also, the current study investigated the influence of a downstream traffic signal only on the occupant injury. The analysis did not consider the effects of the upstream intersection. Further study can incorporate the nearby upstream intersection as well in the analysis. Several classification metrics are known to address the issue of imbalanced data. The current study only adopted the balanced accuracy metric. It will be an opportunity for future work to evaluate other metrics such as F-score, class-weighted evaluation metrics in the

analysis of an imbalanced dataset. It merits referencing that the underreporting of crashes, particularly for least severe crashes is one of the attributes that may bias the results of models developed using historical crash data. Future work may consider variables that relate to vehicle occupants including seating position and occupant status. Besides, pedestrian compliance particularly at signalized intersections is normally impacted by the prevailing traffic and signal characteristics. Thus, it will be an opportunity for future research to investigate factors affecting pedestrian compliance at signalized intersections based on high-resolution event-based data.

doi:<https://doi.org/10.1016/j.aap.2020.105869>. <https://www.sciencedirect.com/science/article/pii/S0001457520316894>.

**Brad's Notes:** Interesting. Really poor sensitivity: 46% for XGBoost and half that for Random Forest.

Kita, Erez, and Gil Luria. "Differences between males and females in the prediction of smartphone use while driving: Mindfulness and income." *Accident Analysis & Prevention* 140 (2020): 105514. doi:<https://doi.org/10.1016/j.aap.2020.105514>. <https://www.sciencedirect.com/science/article/pii/S0001457519312746>.

**Brad's Notes:** Not ML. Small sample size.

Kitali, Angela E., Priyanka Alluri, Thobias Sando, Henrick Haule, Emmanuel Kidando, and Richard Lentz. "Likelihood estimation of secondary crashes using Bayesian complementary log-log model." *Accident Analysis & Prevention* 119 (2018): 58–67. doi:<https://doi.org/10.1016/j.aap.2018.07.003>. <https://www.sciencedirect.com/science/article/pii/S0001457518302999>.

**Brad's Notes:** Too Old

Kjellén, Urban. "The deviation concept in occupational accident control—I: Definition and classification." *Accident Analysis & Prevention* 16, no. 4 (1984): 289–306. doi:[https://doi.org/10.1016/0001-4575\(84\)90023-X](https://doi.org/10.1016/0001-4575(84)90023-X). <https://www.sciencedirect.com/science/article/pii/S000145758490023X>.

**Brad's Notes:** Too Old

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Kong, Xiaoqiang, Subasish Das, Kartikeya Jha, and Yunlong Zhang. "Understanding speeding behavior from naturalistic driving data: Applying classification based association rule mining." *Accident Analysis & Prevention* 144 (2020): 105620. doi:<https://doi.org/10.1016/j.aap.2020.105620>. <https://www.sciencedirect.com/science/article/pii/S0001457519315593>.

Kontaratos, Anthony N. "A systems analysis of the problem of road casualties in the United States." *Accident Analysis & Prevention* 6, no. 3 (1974): 223–241. doi:[https://doi.org/10.1016/0001-4575\(74\)90002-5](https://doi.org/10.1016/0001-4575(74)90002-5). <https://www.sciencedirect.com/science/article/pii/0001457574900025>.

**Brad's Notes:** Too Old

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Krueger, Rico, Prateek Bansal, and Prasad Buddhavarapu. "A new spatial count data model with Bayesian additive regression trees for accident hot spot identification." *Accident Analysis & Prevention* 144 (2020): 105623.

**Suggestions for Future Research:** None ML-related

, doi:<https://doi.org/10.1016/j.aap.2020.105623>. <https://www.sciencedirect.com/science/article/pii/S0001457520306680>.

**Brad's Notes:** Not ML

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Kuo, Jonny, Sjaan Koppel, Judith L. Charlton, and Christina M. Rudin-Brown. "Computer vision and driver distraction: Developing a behaviour-flagging protocol for naturalistic driving data." *Accident Analysis & Prevention* 72 (2014): 177–183. doi:<https://doi.org/10.1016/j.aap.2014.06.007>. <https://www.sciencedirect.com/science/article/pii/S0001457514001808>.

**Brad's Notes:** Too Old

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Kuşkan, Emre, M. Yasin Çodur, and Ahmet Atalay. “Speed violation analysis of heavy vehicles on highways using spatial analysis and machine learning algorithms.” *Accident Analysis & Prevention* 155 (2021): 106098. doi:<https://doi.org/10.1016/j.aap.2021.106098>. <https://www.sciencedirect.com/science/article/pii/S0001457521001299>.

Kwak, Ho-Chan, and Seungyoung Kho. “Predicting crash risk and identifying crash precursors on Korean expressways using loop detector data.” *Accident Analysis & Prevention* 88 (2016): 9–19. doi:<https://doi.org/10.1016/j.aap.2015.12.004>. <https://www.sciencedirect.com/science/article/pii/S0001457515301561>.

**Brad’s Notes:** Too Old

Kwayu, Keneth Morgan, Valerian Kwigizile, Kevin Lee, and Jun-Seok Oh. “Discovering latent themes in traffic fatal crash narratives using text mining analytics and network topology.” *Accident Analysis & Prevention* 150 (2021): 105899. doi:<https://doi.org/10.1016/j.aap.2020.105899>. <https://www.sciencedirect.com/science/article/pii/S000145752031719X>.

**Brad’s Notes:** Not our data. Text analysis of crash reports.

Kwon, Jae-Hong, and Gi-Hyoung Cho. “An examination of the intersection environment associated with perceived crash risk among school-aged children: using street-level imagery and computer vision.” *Accident Analysis & Prevention* 146 (2020): 105716. doi:<https://doi.org/10.1016/j.aap.2020.105716>. <https://www.sciencedirect.com/science/article/pii/S0001457519315398>.

**Brad’s Notes:** Children’s perception of crash risk. Odd.

Lajunen, Timo, and Dianne Parker. "Are aggressive people aggressive drivers? A study of the relationship between self-reported general aggressiveness, driver anger and aggressive driving." *Accident Analysis & Prevention* 33, no. 2 (2001): 243–255. doi:[https://doi.org/10.1016/S0001-4575\(00\)00039-7](https://doi.org/10.1016/S0001-4575(00)00039-7). <https://www.sciencedirect.com/science/article/pii/S0001457500000397>.

**Brad's Notes:** Too Old

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Lam, Lawrence T. "Factors associated with parental safe road behaviour as a pedestrian with young children in metropolitan New South Wales, Australia." *Accident Analysis & Prevention* 33, no. 2 (2001): 203–210. doi:[https://doi.org/10.1016/S0001-4575\(00\)00033-6](https://doi.org/10.1016/S0001-4575(00)00033-6). <https://www.sciencedirect.com/science/article/pii/S0001457500000336>.

**Brad's Notes:** Too Old

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Lavrenz, Steven M., Eleni I. Vlahogianni, Konstantina Gkritza, and Yue Ke. "Time series modeling in traffic safety research." *Accident Analysis & Prevention* 117 (2018): 368–380. doi:<https://doi.org/10.1016/j.aap.2017.11.030>. <https://www.sciencedirect.com/science/article/pii/S0001457517304268>.

**Brad's Notes:** Too Old

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Leu, Sou-Sen, and Ching-Miao Chang. "Bayesian-network-based safety risk assessment for steel construction projects." *Accident Analysis & Prevention* 54 (2013): 122–133. doi:<https://doi.org/10.1016/j.aap.2013.02.019>. <https://www.sciencedirect.com/science/article/pii/S0001457513000602>.

**Brad's Notes:** Too Old

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Li, Feng, Li Jiang, Xiang Yao, and YongJuan Li. “Job demands, job resources and safety outcomes: The roles of emotional exhaustion and safety compliance.” *Accident Analysis & Prevention* 51 (2013): 243–251. doi:<https://doi.org/10.1016/j.aap.2012.11.029>. <https://www.sciencedirect.com/science/article/pii/S0001457512004216>.

**Brad’s Notes:** Too Old

Li, Li, Boxuan Zhong, Clayton Hutmacher, Yulan Liang, William J. Horrey, and Xu Xu. “Detection of driver manual distraction via image-based hand and ear recognition.” *Accident Analysis & Prevention* 137 (2020): 105432. doi:<https://doi.org/10.1016/j.aap.2020.105432>. <https://www.sciencedirect.com/science/article/pii/S0001457519309029>.

**Brad’s Notes:** Not our data. Analyzed images and videos of drivers taken from inside the driving simulator.

Li, Linchao, Carlo G. Prato, and Yonggang Wang. “Ranking contributors to traffic crashes on mountainous freeways from an incomplete dataset: A sequential approach of multivariate imputation by chained equations and random forest classifier.” *Accident Analysis & Prevention* 146 (2020): 105744. doi:<https://doi.org/10.1016/j.aap.2020.105744>. <https://www.sciencedirect.com/science/article/pii/S0001457520315645>.

**Brad’s Notes:** Interesting. How to impute missing data.

Li, Meng, Zhibin Li, Chengcheng Xu, and Tong Liu. “Short-term prediction of safety and operation impacts of lane changes in oscillations with empirical vehicle trajectories.” *Accident Analysis & Prevention* 135 (2020): 105345. doi:<https://doi.org/10.1016/j.aap.2019.105345>. <https://www.sciencedirect.com/science/article/pii/S0001457519305019>.

Li, Pei, Mohamed Abdel-Aty, Qing Cai, and Cheng Yuan. “This paper has been handled by associate editor Tony Sze. The application of novel connected vehicles emulated data on real-time crash potential prediction for arterials.” *Accident Analysis & Prevention* 144 (2020): 105658.

**Suggestions for Future Research:** There are still several improvements that can be done in the future. First, buses are one type of vehicles. It is very promising to explore the fusion with other types vehicles, such as taxis, private vehicles, trucks, etc. Second, the impact of the different variables on crash potential prediction also needs further investigation, a proper variables generation and selection process could possibly improve the performance of the model. Forth, different deep learning architectures can be explored in the future to improve the results of the current model. Finally, it would be promising to combine the results from this paper with other similar studies. For example, Wiseman and Grinberg (2016) proposed a real-time crash potential damages assessment approach for autonomous vehicles. If an autonomous vehicle can receive the crash potential prediction results through CV as suggested in our paper, the information may help it to avoid certain crashes. For the case of inevitable crash, the crash potential damages assessment can help the vehicle achieve the least damages.

doi:<https://doi.org/10.1016/j.aap.2020.105658>. <https://www.sciencedirect.com/science/article/pii/S0001457520305339>.

**Brad’s Notes:** Predict crash potential in the next 5-10 minutes using GPS data.

Li, Pei, Mohamed Abdel-Aty, and Jinghui Yuan. “Real-time crash risk prediction on arterials based on LSTM-CNN.” *Accident Analysis & Prevention* 135 (2020): 105371. doi:<https://doi.org/10.1016/j.aap.2019.105371>. <https://www.sciencedirect.com/science/article/pii/S0001457519311108>.

**Brad’s Notes:** Interesting. Similar, with SMOTE.

Li, Xiaomeng, Atiyeh Vaezipour, Andry Rakotonirainy, and Sebastien Demmel. “Effects of an in-vehicle eco-safe driving system on drivers’ glance behaviour.” *Accident Analysis & Prevention* 122 (2019): 143–152. doi:<https://doi.org/10.1016/j.aap.2018.10.007>. <https://www.sciencedirect.com/science/article/pii/S0001457518308169>.

**Brad’s Notes:** Not ML. Not our data.

Li, Xiaomeng, Atiyeh Vaezipour, Andry Rakotonirainy, Sébastien Demmel, and Oscar Oviedo-Trespalacios. “Exploring drivers’ mental workload and visual demand while using an in-vehicle HMI for eco-safe driving.” *Accident Analysis & Prevention* 146 (2020): 105756. doi:<https://doi.org/10.1016/j.aap.2020.105756>. <https://www.sciencedirect.com/science/article/pii/S0001457520315761>.

**Brad’s Notes:** Not ML

Li, Xiugang, Dominique Lord, Yunlong Zhang, and Yuanchang Xie. “Predicting motor vehicle crashes using Support Vector Machine models.” *Accident Analysis & Prevention* 40, no. 4 (2008): 1611–1618. doi:<https://doi.org/10.1016/j.aap.2008.04.010>. <https://www.sciencedirect.com/science/article/pii/S0001457508000808>.

**Brad’s Notes:** Too Old

Li, Yunjie, Dongfang Ma, Mengtao Zhu, Ziqiang Zeng, and Yinhai Wang. “Identification of significant factors in fatal-injury highway crashes using genetic algorithm and neural network.” *Accident Analysis & Prevention* 111 (2018): 354–363. doi:<https://doi.org/10.1016/j.aap.2017.11.028>. <https://www.sciencedirect.com/science/article/pii/S0001457517304244>.

Li, Zhibin, Pan Liu, Wei Wang, and Chengcheng Xu. “Using support vector machine models for crash injury severity analysis.” *Accident Analysis & Prevention* 45 (2012): 478–486. doi:<https://doi.org/10.1016/j.aap.2011.08.016>. <https://www.sciencedirect.com/science/article/pii/S0001457511002363>.



**Brad's Notes:** Too Old

Lian, Yanqi, Guoqing Zhang, Jaeyoung Lee, and Helai Huang. "Review on big data applications in safety research of intelligent transportation systems and connected/automated vehicles." *Accident Analysis & Prevention* 146 (2020): 105711. doi:<https://doi.org/10.1016/j.aap.2020.105711>. <https://www.sciencedirect.com/science/article/pii/S0001457520307442>.

Liang, Yulan, William J. Horrey, Mark E. Howard, Michael L. Lee, Clare Anderson, Michael S. Shreeve, Conor S. O'Brien, and Charles A. Czeisler. "Prediction of drowsiness events in night shift workers during morning driving." 10th International Conference on Managing Fatigue: Managing Fatigue to Improve Safety, Wellness, and Effectiveness". *Accident Analysis & Prevention* 126 (2019): 105–114. doi:<https://doi.org/10.1016/j.aap.2017.11.004>. <https://www.sciencedirect.com/science/article/pii/S0001457517303913>.

**Brad's Notes:** Not ML, not our data.

Al-libawy, Hilal, Ali Al-Ataby, Waleed Al-Nuaimy, and Majid A. Al-Tae. "Modular design of fatigue detection in naturalistic driving environments." *Accident Analysis & Prevention* 120 (2018): 188–194. doi:<https://doi.org/10.1016/j.aap.2018.08.012>. <https://www.sciencedirect.com/science/article/pii/S0001457518304639>.

**Brad's Notes:** Too Old

Lin, Lei, Qian Wang, and Adel W. Sadek. "A combined M5P tree and hazard-based duration model for predicting urban freeway traffic accident durations." *Accident Analysis & Prevention* 91 (2016): 114–126.

**Suggestions for Future Research:** For future research, one possible idea to investigate, involves combining the M5P tree algorithm with a random parameter HBDM. This may further improve accident duration prediction, by allowing the coefficients of the variables in the model to vary across each individual observation in the dataset. Another possible idea is to test the transferability of M5P-HBDM by building a unique model for two or more datasets.

doi:<https://doi.org/10.1016/j.aap.2016.03.001>. <https://www.sciencedirect.com/science/article/pii/S0001457516300665>.

**Brad's Notes:** Too Old. Not ML

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Lin, Yi, Linchao Li, Hailong Jing, Bin Ran, and Dongye Sun. "Automated traffic incident detection with a smaller dataset based on generative adversarial networks." *Accident Analysis & Prevention* 144 (2020): 105628.

**Suggestions for Future Research:** Notably, only the SVM was applied as the incident detection model to evaluate the proposed method in this paper. In the future, more incident detection models should be implemented to test the proposed method. Moreover, the traffic flow of urban roads is more complex. The application of our proposed method in this area needs to be discussed in the future.

doi:<https://doi.org/10.1016/j.aap.2020.105628>. <https://www.sciencedirect.com/science/article/pii/S0001457519314150>.

**Brad's Notes:** Very Interesting. Small dataset, imbalanced data, Real-time incident detection

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Lin, Yunduan, and Ruimin Li. "Real-time traffic accidents post-impact prediction: Based on crowdsourcing data." *Accident Analysis & Prevention* 145 (2020): 105696. doi:<https://doi.org/10.1016/j.aap.2020.105696>. <https://www.sciencedirect.com/science/article/pii/S0001457520305807>.

**Brad's Notes:** Not our data.

Liu, Jun, Xiaobing Li, and Asad J. Khattak. “An integrated spatio-temporal approach to examine the consequences of driving under the influence (DUI) in crashes.” *Accident Analysis & Prevention* 146 (2020): 105742. doi:<https://doi.org/10.1016/j.aap.2020.105742>. <https://www.sciencedirect.com/science/article/pii/S0001457520315621>.

**Brad’s Notes:** Not ML

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Liu, Jundi, Linda N. Boyle, and Ashis G. Banerjee. “Predicting interstate motor carrier crash rate level using classification models.” *Accident Analysis & Prevention* 120 (2018): 211–218. doi:<https://doi.org/10.1016/j.aap.2018.06.005>. <https://www.sciencedirect.com/science/article/pii/S0001457518302227>.

**Brad’s Notes:** Too Old

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Lourens, Peter F. “Error analysis and applications in transportation systems.” *Accident Analysis & Prevention* 21, no. 5 (1989): 419–426. doi:[https://doi.org/10.1016/0001-4575\(89\)90002-X](https://doi.org/10.1016/0001-4575(89)90002-X). <https://www.sciencedirect.com/science/article/pii/000145758990002X>.

**Brad’s Notes:** Too Old

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Luan, Sen, Meng Li, Xin Li, and Xiaolei Ma. “Effects of built environment on bicycle wrong Way riding behavior: A data-driven approach.” *Accident Analysis & Prevention* 144 (2020): 105613. doi:<https://doi.org/10.1016/j.aap.2020.105613>. <https://www.sciencedirect.com/science/article/pii/S0001457519314241>.

**Brad’s Notes:** Interesting for clear description of method. Homework. Not our data

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Luo, Ruikun, Yifan Weng, Yifan Wang, Paramsothy Jayakumar, Mark J. Brudnak, Victor Paul, Vishnu R. Desaraju, Jeffrey L. Stein, Tulga Ersal, and X. Jessie Yang. “A workload adaptive haptic shared control scheme for semi-autonomous driving.” *Accident Analysis & Prevention* 152 (2021): 105968.

**Suggestions for Future Research:** this study focuses on only a single-vehicle scenario with fixed speed. Further research should extend to a mixed-traffic scenario with varying speeds. When other vehicles are present in the environment, the impact from interactions with them will be important and can be captured with various control schemes (Kerner, 2021, 2018b,a). In addition, the impact of various surveillance tasks can also affect the performance when mixed-traffic is considered. Studying these combined effects is subject to future research.  
doi:<https://doi.org/10.1016/j.aap.2020.105968>. <https://www.sciencedirect.com/science/article/pii/S0001457520317887>.

**Brad's Notes:** Not ML

Luria, Gil. "The social aspects of safety management: Trust and safety climate." *Accident Analysis & Prevention* 42, no. 4 (2010): 1288–1295.  
doi:<https://doi.org/10.1016/j.aap.2010.02.006>. <https://www.sciencedirect.com/science/article/pii/S0001457510000515>.

**Brad's Notes:** Too Old

Lym, Youngbin, and Zhenhua Chen. "Influence of built environment on the severity of vehicle crashes caused by distracted driving: A multi-state comparison." *Accident Analysis & Prevention* 150 (2021): 105920.

**Suggestions for Future Research:** One should note that this study has several limitations that should be further improved in future research. Different from Oviedo-Trespalacios et al. (2020), our assessment was based on the GOL model, which only allowed us to capture the heterogeneity among various states and the heterogeneous influences of built environments on the severity of DD crashes. Hence, the results should be read with a caution, given that the study only presents the influence of the fixed effects (mean structure), whereas we did not consider the unobserved heterogeneity and/or random fluctuation from missing covariates. Therefore, future research could be expanded by adopting more advanced modeling frameworks, such as the generalized additive model and generalized linear mixed model to address non-linear relationships by smoothing functions and random effects such as unobserved heterogeneity (Faraway, 2016). In addition, a latent segmentation-based

ordered logit (LSOL) model may also be adopted to capture heterogeneity or variation in crash severity levels (Fatmi and Habib, 2019). Last but not least, while the analysis was based on standardized data of various states for comparison, it is worth noting that distracted driving behavior tends to be underreported. Therefore, the pattern revealed in this study may not fully capture the actual DD related crashes. Future research should also focus on the utilization of different data sources, such as the telematics data with integration of crash data in order to provide a more comprehensive understanding of the DD driving behavior.

doi:<https://doi.org/10.1016/j.aap.2020.105920>. <https://www.sciencedirect.com/science/article/pii/S0001457520317401>.

**Brad's Notes:** Not ML. Not our data.

Ma, Yongfeng, Wenlu Li, Kun Tang, Ziyu Zhang, and Shuyan Chen. "Driving style recognition and comparisons among driving tasks based on driver behavior in the online car-hailing industry." *Accident Analysis & Prevention* 154 (2021): 106096. doi:<https://doi.org/10.1016/j.aap.2021.106096>. <https://www.sciencedirect.com/science/article/pii/S0001457521001275>.

**Brad's Notes:** Not our data.

Mannering, Fred L. "Male/female driver characteristics and accident risk: Some new evidence." *Accident Analysis & Prevention* 25, no. 1 (1993): 77–84. doi:[https://doi.org/10.1016/0001-4575\(93\)90098-H](https://doi.org/10.1016/0001-4575(93)90098-H). <https://www.sciencedirect.com/science/article/pii/000145759390098H>.

**Brad's Notes:** Too Old

Marucci-Wellman, Helen R., Helen L. Corns, and Mark R. Lehto. "Classifying injury narratives of large administrative databases for surveillance—A practical approach combining machine learning ensembles and human review." *Accident Analysis & Prevention* 98 (2017): 359–371. doi:<https://doi.org/10.1016/j.aap.2016.10.014>. <https://www.sciencedirect.com/science/article/pii/S000145751630375X>.

**Brad's Notes:** Too Old

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Mbaye, Safiétou, and Dongo Rémi Kouabenan. "Effects of the feeling of invulnerability and the feeling of control on motivation to participate in experience-based analysis, by type of risk." *Accident Analysis & Prevention* 51 (2013): 310–317. doi:<https://doi.org/10.1016/j.aap.2012.11.026>. <https://www.sciencedirect.com/science/article/pii/S0001457512004174>.

**Brad's Notes:** Too Old

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McDonald, Anthony D., John D. Lee, Chris Schwarz, and Timothy L. Brown. "A contextual and temporal algorithm for driver drowsiness detection." *Accident Analysis & Prevention* 113 (2018): 25–37.

**Suggestions for Future Research:** None

, doi:<https://doi.org/10.1016/j.aap.2018.01.005>. <https://www.sciencedirect.com/science/article/pii/S0001457518300058>.

**Brad's Notes:** Too Old. Random Forest for feature generation. Only 72 data points. Interesting for extensive description of other algorithms and lit review.

McKenzie, Kirsten, Deborah Anne Scott, Margaret Ann Campbell, and Roderick John McClure. "The use of narrative text for injury surveillance research: A systematic review." *Accident Analysis & Prevention* 42, no. 2 (2010): 354–363. doi:<https://doi.org/10.1016/j.aap.2009.09.020>. <https://www.sciencedirect.com/science/article/pii/S0001457509002589>.

**Brad's Notes:** Too Old

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Mekky, Ali. "Road traffic accidents in rich developing countries: The case of Libya." *Accident Analysis & Prevention* 16, no. 4 (1984): 263–277. doi:[https://doi.org/10.1016/0001-4575\(84\)90021-6](https://doi.org/10.1016/0001-4575(84)90021-6). <https://www.sciencedirect.com/science/article/pii/0001457584900216>.

**Brad’s Notes:** Too Old

Melman, T., J.C.F. de Winter, and D.A. Abbink. “Does haptic steering guidance instigate speeding? A driving simulator study into causes and remedies.” *Accident Analysis & Prevention* 98 (2017): 372–387. doi:<https://doi.org/10.1016/j.aap.2016.10.016>. <https://www.sciencedirect.com/science/article/pii/S0001457516303773>.

**Brad’s Notes:** Too Old

Meng, Qiang, Jinxian Weng, and Xiaobo Qu. “A probabilistic quantitative risk assessment model for the long-term work zone crashes.” *Accident Analysis & Prevention* 42, no. 6 (2010): 1866–1877.

**Suggestions for Future Research:** None

, doi:<https://doi.org/10.1016/j.aap.2010.05.007>. <https://www.sciencedirect.com/science/article/pii/S0001457510001430>.

**Brad’s Notes:** Too Old. Not ML; data set too small.

Mercader, Pedro, and Jack Haddad. “Automatic incident detection on free-ways based on Bluetooth traffic monitoring.” *Accident Analysis & Prevention* 146 (2020): 105703.

**Suggestions for Future Research:** It is also expected that other advanced methods like unsupervised deep learning, see Chalapathy and Chawla (2019), Kwon et al. (2019), may achieve the same or higher detection performance than the proposed method. However, this is at the expense of using a more complex model (large number of parameters) than the proposed in this work. Finally, a caveat of the proposed AID method is that it is able to identify anomalous traffic conditions, but it is not able to distinguish the mechanism that generated these conditions, e.g., traffic accidents, maintenance works, or anomalous traffic patterns. Future works could explore the process of identification of anomalies and posterior classification on data streams by applying novel techniques based on semisupervised learning (Mu et al., 2017; Zhu et al., 2018b).

doi:<https://doi.org/10.1016/j.aap.2020.105703>. <https://www.sciencedirect.com/science/article/pii/S0001457520306837>.

**Brad's Notes:** Primarily about sensors. Not our data set.

Mercurio, D., L. Podofillini, E. Zio, and V.N. Dang. "Identification and classification of dynamic event tree scenarios via possibilistic clustering: Application to a steam generator tube rupture event." *Accident Modelling and Prevention at ESREL 2006, Accident Analysis & Prevention* 41, no. 6 (2009): 1180–1191. doi:<https://doi.org/10.1016/j.aap.2008.08.013>. <https://www.sciencedirect.com/science/article/pii/S0001457508001607>.

**Brad's Notes:** Too Old

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Mohan, Dinesh. "Accidental death and disability in India: A stocktaking." *Accident Analysis & Prevention* 16, no. 4 (1984): 279–288. doi:[https://doi.org/10.1016/0001-4575\(84\)90022-8](https://doi.org/10.1016/0001-4575(84)90022-8). <https://www.sciencedirect.com/science/article/pii/0001457584900228>.

**Brad's Notes:** Too Old

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Montella, Alfonso, Massimo Aria, Antonio D'Ambrosio, and Filomena Mauriello. "Analysis of powered two-wheeler crashes in Italy by classification trees and rules discovery." *PTW + Cognitive impairment and Driving Safety, Accident Analysis & Prevention* 49 (2012): 58–72. doi:<https://doi.org/10.1016/j.aap.2011.04.025>. <https://www.sciencedirect.com/science/article/pii/S000145751100114X>.

**Brad's Notes:** Too Old

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Montella, Alfonso, Filomena Mauriello, Mariano Perneti, and Maria Rella Riccardi. "Rule discovery to identify patterns contributing to overrepresentation and severity of run-off-the-road crashes." *Accident Analysis & Prevention* 155 (2021): 106119. doi:<https://doi.org/10.1016/j.aap.2021.106119>. <https://www.sciencedirect.com/science/article/pii/S0001457521001500>.



Morris, Drew M., June J. Pilcher, and Fred S. Switzer III. "Lane heading difference: An innovative model for drowsy driving detection using retrospective analysis around curves." *Accident Analysis & Prevention* 80 (2015): 117–124. doi:<https://doi.org/10.1016/j.aap.2015.04.007>. <https://www.sciencedirect.com/science/article/pii/S0001457515001360>.

**Brad's Notes:** Too Old

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Moskowitz, Herbert. "Marihuana and driving." *Accident Analysis & Prevention* 17, no. 4 (1985): 323–345. doi:[https://doi.org/10.1016/0001-4575\(85\)90034-X](https://doi.org/10.1016/0001-4575(85)90034-X). <https://www.sciencedirect.com/science/article/pii/000145758590034X>.

**Brad's Notes:** Too Old

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Mujalli, Randa Oqab, Griselda López, and Laura Garach. "Bayes classifiers for imbalanced traffic accidents datasets." *Accident Analysis & Prevention* 88 (2016): 37–51. doi:<https://doi.org/10.1016/j.aap.2015.12.003>. <https://www.sciencedirect.com/science/article/pii/S0001457515301548>.

**Brad's Notes:** Too Old

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Murphy, Lauren A., Michelle M. Robertson, and Pascale Carayon. "The next generation of macroergonomics: Integrating safety climate." Systems thinking in workplace safety and health, *Accident Analysis & Prevention* 68 (2014): 16–24. doi:<https://doi.org/10.1016/j.aap.2013.11.011>. <https://www.sciencedirect.com/science/article/pii/S0001457513004673>.

**Brad's Notes:** Too Old

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Musselwhite, Charles B.A., Erel Avineri, Yusak O. Susilo, and Darren Bhattachary. "Public attitudes towards motorcyclists' safety: A qualitative study from the United Kingdom." *PTW + Cognitive impairment and Driving Safety, Accident Analysis & Prevention* 49 (2012): 105–113. doi:<https://doi.org/10.1016/j.aap.2011.06.005>. <https://www.sciencedirect.com/science/article/pii/S0001457511001710>.

**Brad's Notes:** Too Old

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Mussone, L., M. Bassani, and P. Masci. "Analysis of factors affecting the severity of crashes in urban road intersections." *Accident Analysis & Prevention* 103 (2017): 112–122. doi:<https://doi.org/10.1016/j.aap.2017.04.007>. <https://www.sciencedirect.com/science/article/pii/S0001457517301355>.

**Brad's Notes:** Too Old

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Naderpour, Mohsen, Jie Lu, and Guangquan Zhang. "The explosion at institute: Modeling and analyzing the situation awareness factor." *Accident Analysis & Prevention* 73 (2014): 209–224. doi:<https://doi.org/10.1016/j.aap.2014.09.008>. <https://www.sciencedirect.com/science/article/pii/S0001457514002644>.

**Brad's Notes:** Too Old

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Nanda, Gaurav, Kirsten Vallmuur, and Mark Lehto. "Improving autocoding performance of rare categories in injury classification: Is more training data or filtering the solution?" *Accident Analysis & Prevention* 110 (2018): 115–127. doi:<https://doi.org/10.1016/j.aap.2017.10.020>. <https://www.sciencedirect.com/science/article/pii/S0001457517303767>.

**Brad's Notes:** Too Old

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Naujoks, Frederik, Simon Höfling, Christian Purucker, and Kathrin Zeeb. “From partial and high automation to manual driving: Relationship between non-driving related tasks, drowsiness and take-over performance.” *Accident Analysis & Prevention* 121 (2018): 28–42. doi:<https://doi.org/10.1016/j.aap.2018.08.018>. <https://www.sciencedirect.com/science/article/pii/S0001457518303944>.

**Brad’s Notes:** Too Old

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Naujoks, Frederik, Andrea Kiesel, and Alexandra Neukum. “Cooperative warning systems: The impact of false and unnecessary alarms on drivers’ compliance.” *Accident Analysis & Prevention* 97 (2016): 162–175. doi:<https://doi.org/10.1016/j.aap.2016.09.009>. <https://www.sciencedirect.com/science/article/pii/S0001457516303396>.

**Brad’s Notes:** Too Old

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Naujoks, Frederik, Christian Purucker, Katharina Wiedemann, Alexandra Neukum, Stefan Wolter, and Reid Steiger. “Driving performance at lateral system limits during partially automated driving.” *Accident Analysis & Prevention* 108 (2017): 147–162. doi:<https://doi.org/10.1016/j.aap.2017.08.027>. <https://www.sciencedirect.com/science/article/pii/S000145751730307X>.

**Brad’s Notes:** Too Old

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Niskanen, Toivo. “Assessing the safety environment in work organization of road maintenance jobs.” *Accident Analysis & Prevention* 26, no. 1 (1994): 27–39. doi:[https://doi.org/10.1016/0001-4575\(94\)90066-3](https://doi.org/10.1016/0001-4575(94)90066-3). <https://www.sciencedirect.com/science/article/pii/0001457594900663>.

**Brad’s Notes:** Too Old

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Onken, R., and J.P. Feraric. “Adaptation to the driver as part of a driver monitoring and warning system.” *Fatigue and Transport, Accident Analysis & Prevention* 29, no. 4 (1997): 507–513. doi:[https://doi.org/10.1016/S0001-4575\(97\)00030-4](https://doi.org/10.1016/S0001-4575(97)00030-4). <https://www.sciencedirect.com/science/article/pii/S0001457597000304>.

**Brad’s Notes:** Too Old

Osman, Osama A., Mustafa Hajij, Sogand Karbalaieali, and Sherif Ishak. “A hierarchical machine learning classification approach for secondary task identification from observed driving behavior data.” *Accident Analysis & Prevention* 123 (2019): 274–281.

**Suggestions for Future Research:** It is worth pointing out that this study did not account for the effect of roadway type and geometric features and vehicle characteristics on the driving behavior variables. However, the driving behavior variables are analyzed as a pattern recognition problem in this study. In other words, identification of secondary tasks is performed through studying the pattern of changes in the driving behavior variables, rather than targeting specific values of each variable as indicators of the type of secondary task drivers are engaged in. Nonetheless, future research will study the impact of roadway type and geometric features and vehicle characteristics on driving behavior variables, hence on the predictability power of the developed models. doi:<https://doi.org/10.1016/j.aap.2018.12.005>. <https://www.sciencedirect.com/science/article/pii/S000145751831114X>.

**Brad’s Notes:** Interesting in that it looked much more deeply at the data than other studies, looking for correlations between sets of variables. I would like to know about this SHRP-2

Oviedo-Trespalacios, Oscar, Md Mazharul Haque, Mark King, and Sebastien Demmel. “Driving behaviour while self-regulating mobile phone interactions: A human-machine system approach.” *Accident Analysis & Prevention* 118 (2018): 253–262. doi:<https://doi.org/10.1016/j.aap.2018.03.020>. <https://www.sciencedirect.com/science/article/pii/S0001457518301246>.

**Brad’s Notes: Too Old**

Oviedo-Trespalcios, Oscar, Md. Mazharul Haque, Mark King, and Simon Washington. “Effects of road infrastructure and traffic complexity in speed adaptation behaviour of distracted drivers.” *Accident Analysis & Prevention* 101 (2017): 67–77. doi:<https://doi.org/10.1016/j.aap.2017.01.018>. <https://www.sciencedirect.com/science/article/pii/S0001457517300453>.

**Brad’s Notes: Too Old**

Oviedo-Trespalcios, Oscar, Verity Truelove, and Mark King. ““It is frustrating to not have control even though I know it’s not legal!”: A mixed-methods investigation on applications to prevent mobile phone use while driving.” *Accident Analysis & Prevention* 137 (2020): 105412. doi:<https://doi.org/10.1016/j.aap.2019.105412>. <https://www.sciencedirect.com/science/article/pii/S0001457519316525>.

**Brad’s Notes: Not ML**

Paez, Antonio, Hany Hassan, Mark Ferguson, and Saiedeh Razavi. “A systematic assessment of the use of opponent variables, data subsetting and hierarchical specification in two-party crash severity analysis.” *Accident Analysis & Prevention* 144 (2020): 105666.

**Suggestions for Future Research:** The analysis also opens up a few avenues for future research. First, for reasons discussed in Section 6, we did not consider more sophisticated modelling approaches, such as models with random components, partial proportional odds, ranked ordered models, or multinomial models, to mention just a few possibilities. Secondly, we only considered the performance of the models when making predictions for the full sample. That is, the submodels in the ensembles were not compared in detail, just their aggregate results when predicting the full sample. However, the goodness-of-fit was not uniformly better for any one modelling strategy when the data were subset, and it is possible that individual models perform better for a certain subset than competitors that are part of a better ensemble, overall. For this reason, we suggest that additional work with ensemble approaches

is warranted. Finally, it is clear that the models do not generally do well when predicting the least frequent class of outcome, namely Fatality. It would be worthwhile to further investigate approaches for so-called imbalanced learning, a task that has received attention in the machine learning community (e.g., Haixiang et al., 2017; He and Garcia, 2009), and where Torrao et al. (2014) have already made some headway in crash severity analysis.

doi:<https://doi.org/10.1016/j.aap.2020.105666>. <https://www.sciencedirect.com/science/article/pii/S0001457520303298>.

**Brad’s Notes:** Interesting for solid paper.

Pariota, Luigi, Gennaro Nicola Bifulco, Francesco Galante, Alfonso Montella, and Mark Brackstone. “Longitudinal control behaviour: Analysis and modelling based on experimental surveys in Italy and the UK.” *Accident Analysis & Prevention* 89 (2016): 74–87. doi:<https://doi.org/10.1016/j.aap.2016.01.007>. <https://www.sciencedirect.com/science/article/pii/S0001457516300070>.

**Brad’s Notes:** Too Old

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Park, Hyoshin, Ali Haghani, Siby Samuel, and Michael A. Knodler. “Real-time prediction and avoidance of secondary crashes under unexpected traffic congestion.” *Accident Analysis & Prevention* 112 (2018): 39–49. doi:<https://doi.org/10.1016/j.aap.2017.11.025>. <https://www.sciencedirect.com/science/article/pii/S0001457517304219>.

**Brad’s Notes:** Too Old

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Park, Hyunjin, and Cheol Oh. “A vehicle speed harmonization strategy for minimizing inter-vehicle crash risks.” *Accident Analysis & Prevention* 128 (2019): 230–239.

**Suggestions for Future Research:** Although useful insights were derived from this study, further research needs to be conducted to achieve results with greater reliability. First, there is an opportunity to improve the risk estimation method. Various contributing factors affecting inter-vehicle risks need to be considered when estimating the risk, including adverse weather and road geometric conditions in addition to the vehicle performance. Second, more effective and intelligent techniques for obtaining the target speed should be studied. For example, machine learning techniques that have received much attention recently should be applied and investigated to improve the performance. One feasible alternative is the design of an artificial intelligence controller based on reinforcement learning, which the authors have been working on as a further study. Third, there should be an attempt to obtain the target speed to address multiple other objectives, including the operational efficiency and the environmental impacts, rather than just focusing on the safety. This is because these three objectives are fundamentally determined by individual vehicle maneuverings. Finally, more systematic simulation calibration and validation need to be conducted with a larger vehicle trajectory dataset. Various traffic conditions and vehicle types should also be taken into consideration in comparing the actual data and the simulated data.

doi:<https://doi.org/10.1016/j.aap.2019.04.014>. <https://www.sciencedirect.com/science/article/pii/S0001457519300314>.

**Brad's Notes:** Controlling the speed of vehicles in traffic to keep spacing.

Park, Juneyoung, and Mohamed Abdel-Aty. "Assessing the safety effects of multiple roadside treatments using parametric and nonparametric approaches." *Accident Analysis & Prevention* 83 (2015): 203–213. doi:<https://doi.org/10.1016/j.aap.2015.07.008>. <https://www.sciencedirect.com/science/article/pii/S0001457515300178>.

**Brad's Notes:** Too Old

Parnell, Katie J., Neville A. Stanton, and Katherine L. Plant. "What's the law got to do with it? Legislation regarding in-vehicle technology use and its impact on driver distraction." *Accident Analysis & Prevention* 100 (2017): 1–14. doi:<https://doi.org/10.1016/j.aap.2016.12.015>. <https://www.sciencedirect.com/science/article/pii/S0001457516304535>.

**Brad's Notes:** Too Old

Parsa, Amir Bahador, Ali Movahedi, Homa Taghipour, Sybil Derrible, and Abolfazl (Kouros) Mohammadian. "Toward safer highways, application of XGBoost and SHAP for real-time accident detection and feature analysis." *Accident Analysis & Prevention* 136 (2020): 105405. doi:<https://doi.org/10.1016/j.aap.2019.105405>. <https://www.sciencedirect.com/science/article/pii/S0001457519311790>.

Parsa, Amir Bahador, Homa Taghipour, Sybil Derrible, and Abolfazl (Kouros) Mohammadian. "Real-time accident detection: Coping with imbalanced data." *Accident Analysis & Prevention* 129 (2019): 202–210.

**Suggestions for Future Research:** When attempting to detect accident occurrence, the number of accidents in a dataset tends to be small, and therefore most studies must cope with highly imbalanced data. To further improve model performance, if available, more spatiotemporal data could be used. Finally, as future work, the performance of deep learning models, such as Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN), could be investigated, especially when used alongside techniques to deal with imbalanced data and that create more data such as SMOTE.

doi:<https://doi.org/10.1016/j.aap.2019.05.014>. <https://www.sciencedirect.com/science/article/pii/S0001457519301642>.

**Brad's Notes:** Not prediction, but identification from real-time data. Also not severity of crash, but just occurrence of a crash. Interesting for discussion of techniques for imbalanced data.



Patten, Christopher J.D., Albert Kircher, Joakim Östlund, Lena Nilsson, and Ola Svenson. "Driver experience and cognitive workload in different traffic environments." *Accident Analysis & Prevention* 38, no. 5 (2006): 887–894. doi:<https://doi.org/10.1016/j.aap.2006.02.014>. <https://www.sciencedirect.com/science/article/pii/S0001457506000303>.

**Brad's Notes:** Too Old

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Patterson, Jessica M., and Scott A. Shappell. "Operator error and system deficiencies: Analysis of 508 mining incidents and accidents from Queensland, Australia using HFACS." *Accident Analysis & Prevention* 42, no. 4 (2010): 1379–1385. doi:<https://doi.org/10.1016/j.aap.2010.02.018>. <https://www.sciencedirect.com/science/article/pii/S0001457510000643>.

**Brad's Notes:** Too Old

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Peng, Yichuan, Chongyi Li, Ke Wang, Zhen Gao, and Rongjie Yu. "Examining imbalanced classification algorithms in predicting real-time traffic crash risk." *Accident Analysis & Prevention* 144 (2020): 105610. doi:<https://doi.org/10.1016/j.aap.2020.105610>. <https://www.sciencedirect.com/science/article/pii/S0001457519306906>.

**Brad's Notes:** Interesting for comparing algorithms.

Pestonjee, D.M. "Improving performance for safety and health: Kinglsey. Garland STPM Press, New York, 1982. 242 pp. \$35.00." *Accident Analysis & Prevention* 16, no. 2 (1984): 151–152. doi:[https://doi.org/10.1016/0001-4575\(84\)90040-X](https://doi.org/10.1016/0001-4575(84)90040-X). <https://www.sciencedirect.com/science/article/pii/000145758490040X>.

**Brad's Notes:** Too Old

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Petraki, Virginia, Apostolos Ziakopoulos, and George Yannis. "Combined impact of road and traffic characteristic on driver behavior using smart-phone sensor data." *Accident Analysis & Prevention* 144 (2020): 105657.

**Suggestions for Future Research:** The results of this study may be transferred to similar areas outside the research area. However, prior to any generalization, necessary adjustments should be made for possible variations in the road environment and traffic. For instance, an analogous study should be conducted for motorways or rural roads that have fundamentally different characteristics than urban expressways in order to obtain more accurate results for these road environments. Alternative count models such as GLMs with known merits for similar research or machine learning methods should also be investigated. Initial Poisson loglinear model applications have shown that the discovered relationships are retained in significance and sign (positive or negative influences). Intuitively, several crash frequency methods found in the rich road safety literature have the potential to be applied in harsh event investigation, and the respective findings will augment and expand the knowledge obtained from strictly analyzing crashes. Furthermore, a very promising direction for future research would be the investigation of crash numbers and locations in the same research areas. It would be fruitful to test correlations of crash frequencies with some of the variables that have been identified in the present study, and to explore any correlations between harsh event frequencies and crash frequencies as well. However, it is worth noting that this endeavor requires significant updates in crash data collection procedures in Greece, as crash locations tend to be very imprecise compared to high-resolution smartphone data. A similar conundrum rises when weather data are brought into consideration. The inclusion of weather data in the present context would be quite interesting, as there can be considered to be related to crashes from research (Theofilatos and Yannis, 2014), and to harsh events from observation and experience. However, the high resolution smartphone data utilized in the study would be best paired with comparably high resolution weather data, which are at present not readily available. Therefore, further research is needed to create a proper smartphone naturalistic driving data and weather data merging scheme, which will yield usable results towards this direction.

doi:<https://doi.org/10.1016/j.aap.2020.105657>. <https://www.sciencedirect.com/science/article/pii/S0001457519315933>.

**Brad's Notes:** Not ML, Smartphone Data

Pramanik, Anima, Sobhan Sarkar, and J. Maiti. “A real-time video surveillance system for traffic pre-events detection.” *Accident Analysis & Prevention* 154 (2021): 106019. doi:<https://doi.org/10.1016/j.aap.2021.106019>. <https://www.sciencedirect.com/science/article/pii/S0001457521000506>.

Putnam, Jacob B., Jeffrey T. Somers, Jessica A. Wells, Chris E. Perry, and Costin D. Untaroiu. “Development and evaluation of a finite element model of the THOR for occupant protection of spaceflight crewmembers.” *Accident Analysis & Prevention* 82 (2015): 244–256. doi:<https://doi.org/10.1016/j.aap.2015.05.002>. <https://www.sciencedirect.com/science/article/pii/S0001457515001797>.

#### **Brad’s Notes: Too Old**

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Qiao, Si, Anthony Gar-On Yeh, Mengzhu Zhang, and Xiang Yan. “Effects of state-led suburbanization on traffic crash density in China: Evidence from the Chengdu City Proper.” *Accident Analysis & Prevention* 148 (2020): 105775. doi:<https://doi.org/10.1016/j.aap.2020.105775>. <https://www.sciencedirect.com/science/article/pii/S0001457520315955>.

#### **Brad’s Notes: Not ML**

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Quddus, Azhar, Ali Shahidi Zandi, Laura Prest, and Felix J.E. Comeau. “Using long short term memory and convolutional neural networks for driver drowsiness detection.” *Accident Analysis & Prevention* 156 (2021): 106107. doi:<https://doi.org/10.1016/j.aap.2021.106107>. <https://www.sciencedirect.com/science/article/pii/S000145752100138X>.

Rahim, Md Adilur, and Hany M. Hassan. “A deep learning based traffic crash severity prediction framework.” *Accident Analysis & Prevention* 154 (2021): 106090.

**Suggestions for Future Research:** Future studies may further tune the weight parameter ( $\beta$ ) of the loss function and the threshold value for classifiers to get more optimized precision and recall values suitable for real-life applications.

doi:<https://doi.org/10.1016/j.aap.2021.106090>. <https://www.sciencedirect.com/science/article/pii/S0001457521001214>.

**Brad's Notes:** Interesting

Starts off seeming like it's going to be about real-time crash prediction, but then only uses old data, 2014-2018.

Crash severity prediction model.

Talks about different metrics: Precision, Recall, Accuracy, Cross-entropy loss. In an imbalanced dataset, accuracy places more weight on the common classes than in the rare classes. Precision and recall penalize a model for ignoring the minority classes.

This paper's method emphasizes the recall value of the fatal crashes, because we can allow false positives (non-fatal crashes predicted as fatal) but not false negatives (fatal crashes predicted as non-fatal).

Transformed numerical data to images, then used CNN, which usually (a) extracts features from the images and (b) classifies the images. They used transfer learning to do the feature extraction.

Compared CNN with the weird image transformation to SVN.

Statistical Learning and ML models compared in lit review:

(SVM) Support Vector Machine,  
(OP) Ordered Probit,  
Logistic Regression,  
(CART) Classification and Regression Tree  
Abdel-Aty used a variable selection procedure prior to model estimation  
(?)  
(BLR) Bayesian Logistic Regression,  
(ROC) Receiver Operating Characteristic Metric,  
(AUC) Area Under Curve, especially under ROC curve,

SVM with Radial-basis kernel function,  
 SVM with the polynomial kernel outperformed the Gaussian radial basis kernel,  
 (ANN) Artificial Neural Network compared to Ordered Probit,  
*k*-means algorithm clustered the dataset into three clusters to improve ANN's performance,  
 Random Forest outperformed Logistic Regression, Naive Bayes, and AdaBoost,  
 (LSTM) Long Short-Term Memory beat (MLP) Multilayer Perceptron and (BLR) Bayesian Logistic Regression.

Zheng (2019)

(CNN) Convolutional Neural Network used (FM2GI) Feature Matrix to Gray Image algorithm to convert traffic accident data to gray images to be input for the image classification model.

Cross-entropy loss used with Adam optimizer to optimize the model.

(SMOTE) Synthetic Minority Oversampling Technique used to deal with an imbalanced dataset.

(STCL-Net) Spatiotemporal Convolutional Long Short-term Memory Network beat benchmark models in (MSE) Mean Squared Error, (MAE) Mean Absolute Error, and (MAPE) Mean Absolute Percentage Error metrics.

CNN with dropout operation (What is that?) performed better than shallow models (what are those?)

(LSTM-CNN) Long Short-Term Memory Convolutional Neural Network outperformed LSTM, CNN, XGBoost, BLR in terms of sensitivity and false alarm rate.

(R-CNN) Region-based Convolutional Neural Networks

(DNN) Deep Neural Network predicted traffic conflicts in real time with high prediction accuracy and sensitivity, and low false alarm rate.

(LSTMDTR) LSTM models for (DTR) Different Temporal Resolutions. Number of neurons in the model affected performance and computation time.

CNN and (GRU) Gated Recurrent Units combined to make a fusion model.

## Data

Louisiana DOTD data, 2014-2018, 10,048 crashes with 98 variables.  
 Why so few crashes?

42 fatal, 2699 injury, 7307 (PDO) Property Damage Only

### Data Cleaning

Long section on how the authors cleaned the data.

Took out records with missing or inconsistent data, rather than fixing them.

Long list of types of records they considered inconsistent.

Final dataset had 33 fatal, 1806 injury, and 4497 PDO, total 6336.

Removed  $(42 - 33)/42 = 9/42 = 21\%$  of fatal,  $(2699 - 1806)/2699 = 893/2699 = 33\%$  of injury,  $(7307 - 4497)/7307 = 2810/7307 = 38\%$  of PDO, and  $(10048 - 6336)/10048 = 3712/10048 = 37\%$  total.

**Variable Selection** Use (CART) Classification and Regression Tree and (MARS) Multivariate Adaptive Regression Spline to select the variables that have significant associations with the dependent variable (crash severity). CART returned ten significant variables; MARS, twelve.

### Transfer Learning

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Read, Gemma J.M., Michael G. Lenné, and Simon A. Moss. “Associations between task, training and social environmental factors and error types involved in rail incidents and accidents.” Intelligent Speed Adaptation + Construction Projects, *Accident Analysis & Prevention* 48 (2012): 416–422. doi:<https://doi.org/10.1016/j.aap.2012.02.014>. <https://www.sciencedirect.com/science/article/pii/S0001457512000802>.

### Brad’s Notes: Too Old

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Reiman, Teemu, and Carl Rollenhagen. “Does the concept of safety culture help or hinder systems thinking in safety?” Systems thinking in workplace safety and health, *Accident Analysis & Prevention* 68 (2014): 5–15. doi:<https://doi.org/10.1016/j.aap.2013.10.033>. <https://www.sciencedirect.com/science/article/pii/S0001457513004430>.

### Brad’s Notes: Too Old

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Rezapour, Mahdi, Khaled Ksaibati, and Milhan Moomen. “Application of Quantile Mixed Model for modeling Traffic Barrier Crash Cost.” *Accident Analysis & Prevention* 148 (2020): 105795.

**Suggestions for Future Research:** For this study we just considered barriers with crashes as barriers with no crashes did not have drivers' characteristic such as alcohol involvement, or citation record as a crash has not been occurred. Inclusion of barriers with no crashes is important in the state as much of the barriers are not based on recommended designs, and much of them have not experienced any crash. To achieve the aforementioned criteria the following analysis could be considered in the future studies to incorporate barriers with no crashes as follows: 1 It is possible to only consider variables that are similar across barriers with crashes and with no crashes. Those included predictors such as barriers' types, geometric characteristics, traffic, and barrier length. That model could be implemented on both barriers with and without crashes. 2 Instead of using cost as response, EPDO could be used. For this type of response various model such as negative binomial could be conducted on both barriers with and without crashes. 3 As negative binomial might not perform optimally for excess number of zeroes, two component models, hurdle or zero-inflated models, are expected to perform better. Those two-component models would have two layers: one model for barriers with zero count crashes and one model for barriers with crashes. In order to account for grouping factor that we considered in this study; hierarchical model could be a closest model to the implemented model in those studies. As discussed, after identification of factors to barriers 'crashes, the final objective is to conduct cost-benefit analysis. This would be implemented through quantile machine learning technique. The algorithm would be trained over the original dataset. Then, variables especially barriers geometric characteristics, such as barriers' height would be optimized to their optimal values. The trained model would be implemented again over a new dataset and cost-benefit output would be estimated. For instance, barriers' optimum height is 27 inches for box-beam. In many places, the barriers' height is less than that value. Thus, first the cost would be predicted based on the barrier current height. Then, the barrier's height would be changed to 27 inches. The trained algorithm would be conducted again, and cost would be predicted. The difference would be the cost/benefit output.

doi:<https://doi.org/10.1016/j.aap.2020.105795>. <https://www.sciencedirect.com/science/article/pii/S0001457520316158>.

**Brad's Notes:** Not ML

Robinson, Gordan H. "Accidents and sociotechnical systems: principles for design." *Accident Analysis & Prevention* 14, no. 2 (1982): 121–130. doi:[https://doi.org/10.1016/0001-4575\(82\)90078-1](https://doi.org/10.1016/0001-4575(82)90078-1). <https://www.sciencedirect.com/science/article/pii/0001457582900781>.

**Brad's Notes:** Too Old

Rocha, Miriam, Michel Anzanello, Felipe Caleffi, Helena Cybis, and Gabrielli Yamashita. "A multivariate-based variable selection framework for clustering traffic conflicts in a brazilian freeway." *Accident Analysis & Prevention* 132 (2019): 105269.

**Suggestions for Future Research:** Future research includes the application of supervised multivariate techniques (e.g., k-Nearest Neighbor or Support Vector Machine) to insert events into categories of conflict severity. The use of the parameters derived from Partial Least Squares regression to build a new variable importance index is also promising.  
doi:<https://doi.org/10.1016/j.aap.2019.105269>. <https://www.sciencedirect.com/science/article/pii/S0001457519305330>.

**Brad's Notes:** Not ML

Roland, Jeremiah, Peter D. Way, Connor Firat, Thanh-Nam Doan, and Mina Sartipi. "Modeling and predicting vehicle accident occurrence in Chattanooga, Tennessee." *Accident Analysis & Prevention* 149 (2021): 105860.



**Suggestions for Future Research:** As the project proceeds, adjustments to the model and its input features will continue to provide the optimal output. One such future branch of this study includes further investigation into the creation of a singular adverse weather variable, as presented by Hebert et al. (2019). The current individual weather binaries presented within this study could be complicating the models unnecessarily, although this is subject to be determined by further testing. Additionally, demographic data as presented in Dan et al. (2018), Yuan et al. (2017) could be accessed from Geographical Information System (GIS) and incorporated into future modelling, providing some of the missing human factors sought by this team. Lastly, regarding the limitation of a lack of data, any future implementations of this project in different cities/counties could potentially benefit from additional roadway or driver specific data should that city/county have access to said data.

doi:<https://doi.org/10.1016/j.aap.2020.105860>. <https://www.sciencedirect.com/science/article/pii/S0001457520316808>.

**Brad's Notes:** Straightforward. Live app for local police.

Created negative samples.

Ran feature selection, but it selected some weather variables that correlate to the time of day, like humidity, uvIndex, temperature, dewPoint, pressure, and visibility, and excluded Rain/cloudy/foggy/show/clear, Rain in previous hour, and Precipitation intensity.

Weird argument for having redundant variables.

“Regarding Test A yielding the most viable results, the inclusion of potentially redundant variables (e.g., Lat/Long and Grid\_Num or Hour and DayFrame) is not detrimental to the model’s usability, as those potentially redundant variables use different scales. For example, latitude and longitude use the standard GPS coordinate scale, while Grid\_Num is an integer from 1 to 694. In other words, while some of the variables may reflect similar information, they are presented in inherently different ways.”

I’m confused about how you can provide all available variables while applying feature selection. Aren’t those contradictory?

“The best performing accident prediction model resulted from changing the hour, date, and location values of an accident entry when creating

negative samples, having an even split of negative to positive data, providing all available variables for analysis, and applying feature selection, referred to as Total Shift 50–50 FS TA.”

Roque, Carlos, and Mohammad Jalayer. “Improving roadside design policies for safety enhancement using hazard-based duration modeling.” *Accident Analysis & Prevention* 120 (2018): 165–173. doi:<https://doi.org/10.1016/j.aap.2018.08.008>. <https://www.sciencedirect.com/science/article/pii/S0001457518304305>.

**Brad’s Notes:** Too Old

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Rosenbloom, Tova, and Yuval Wolf. “Signal detection in conditions of everyday life traffic dilemmas.” *Accident Analysis & Prevention* 34, no. 6 (2002): 763–772. doi:[https://doi.org/10.1016/S0001-4575\(01\)00076-8](https://doi.org/10.1016/S0001-4575(01)00076-8). <https://www.sciencedirect.com/science/article/pii/S0001457501000768>.

**Brad’s Notes:** Too Old

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Ross, Lesley A., Erica L. Schmidt, and Karlene Ball. “Interventions to maintain mobility: What works?” Emerging Research Methods and Their Application to Road Safety Emerging Issues in Safe and Sustainable Mobility for Older Persons The Candrive/Ozcandrive Prospective Older Driver Study: Methodology and Early Study Findings, *Accident Analysis & Prevention* 61 (2013): 167–196. doi:<https://doi.org/10.1016/j.aap.2012.09.027>. <https://www.sciencedirect.com/science/article/pii/S0001457512003442>.

**Brad’s Notes:** Too Old

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Rouzikhah, Hossein, Mark King, and Andry Rakotonirainy. “Examining the effects of an eco-driving message on driver distraction.” *Accident Analysis & Prevention* 50 (2013): 975–983. doi:<https://doi.org/10.1016/j.aap.2012.07.024>. <https://www.sciencedirect.com/science/article/pii/S0001457512002862>.

**Brad's Notes: Too Old**

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Rupp, Michael A., Marc D. Gentzler, and Janan A. Smither. "Driving under the influence of distraction: Examining dissociations between risk perception and engagement in distracted driving." *Accident Analysis & Prevention* 97 (2016): 220–230. doi:<https://doi.org/10.1016/j.aap.2016.09.003>. <https://www.sciencedirect.com/science/article/pii/S0001457516303335>.

**Brad's Notes: Too Old**

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Saari, J.T., and J. Lahtela. "Characteristics of jobs in high and low accident frequency companies in the light metal working industry." *Accident Analysis & Prevention* 11, no. 1 (1979): 51–60. doi:[https://doi.org/10.1016/0001-4575\(79\)90039-3](https://doi.org/10.1016/0001-4575(79)90039-3). <https://www.sciencedirect.com/science/article/pii/0001457579900393>.

**Brad's Notes: Too Old**

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Sagar, Shraddha, Nikiforos Stamatiadis, Samantha Wright, and Aaron Cambron. "Identifying high-risk commercial vehicle drivers using sociodemographic characteristics." *Accident Analysis & Prevention* 143 (2020): 105582. doi:<https://doi.org/10.1016/j.aap.2020.105582>. <https://www.sciencedirect.com/science/article/pii/S0001457520301640>.

**Brad's Notes: Not ML. Not our data**

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Saha, Dibakar, Priyanka Alluri, Eric Dumbaugh, and Albert Gan. "Application of the Poisson-Tweedie distribution in analyzing crash frequency data." *Accident Analysis & Prevention* 137 (2020): 105456. doi:<https://doi.org/10.1016/j.aap.2020.105456>. <https://www.sciencedirect.com/science/article/pii/S0001457519315258>.

**Brad's Notes: Not ML**

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Santos-Reyes, Jaime, and Alan N. Beard. “A systemic analysis of the Edge Hill railway accident.” *Accident Modelling and Prevention at ESREL 2006, Accident Analysis & Prevention* 41, no. 6 (2009): 1133–1144. doi:<https://doi.org/10.1016/j.aap.2008.05.004>. <https://www.sciencedirect.com/science/article/pii/S0001457508000869>.

**Brad’s Notes: Too Old**

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Sarkar, Abhijit, Jeffrey S. Hickman, Anthony D. McDonald, Wenyan Huang, Tobias Vogelpohl, and Gustav Markkula. “Steering or braking avoidance response in SHRP2 rear-end crashes and near-crashes: A decision tree approach.” *Accident Analysis & Prevention* 154 (2021): 106055. doi:<https://doi.org/10.1016/j.aap.2021.106055>. <https://www.sciencedirect.com/science/article/pii/S0001457521000865>.

Savolainen, Peter T. “Examining driver behavior at the onset of yellow in a traffic simulator environment: Comparisons between random parameters and latent class logit models.” *Accident Analysis & Prevention* 96 (2016): 300–307. doi:<https://doi.org/10.1016/j.aap.2016.01.006>. <https://www.sciencedirect.com/science/article/pii/S0001457516300069>.

**Brad’s Notes: Too Old**

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Schlögl, Matthias. “A multivariate analysis of environmental effects on road accident occurrence using a balanced bagging approach.” *Accident Analysis & Prevention* 136 (2020): 105398. doi:<https://doi.org/10.1016/j.aap.2019.105398>. <https://www.sciencedirect.com/science/article/pii/S0001457519308516>.

Schlögl, Matthias, and Rainer Stütz. “Methodological considerations with data uncertainty in road safety analysis.” *Road Safety Data Considerations, Accident Analysis & Prevention* 130 (2019): 136–150. doi:<https://doi.org/10.1016/j.aap.2017.02.001>. <https://www.sciencedirect.com/science/article/pii/S0001457517300519>.

**Brad’s Notes: Questions about Uncertainties in Data**

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Schlögl, Matthias, Rainer Stütz, Gregor Laaha, and Michael Melcher. “A comparison of statistical learning methods for deriving determining factors of accident occurrence from an imbalanced high resolution dataset.” *Accident Analysis & Prevention* 127 (2019): 134–149.

**Suggestions for Future Research:** Having described the modeling approach with a methodological focus, further work should be targeted at a more detailed assessment of the results from a traffic-safety point of view. Therefore, next steps should focus on investigating whose sections’ outcome is captured well, and shed some light on the why. In addition, further analysis featuring variants of bootstrap aggregating could be useful for improving the robustness of the results. We propose several concrete analysis steps for this empirical assessment: Further temporal aggregation: Given the assumption that results obtained from any learners applied to the dataset featuring hourly values are subject to uncertainty, the temporal binning size could be adjusted in order to create coarser, yet more robust aggregates. These aggregated data could be used to test the hypothesis that the significance of results would increase with increasing binning level. While some information is lost, since variables related to some sort of timestamp (i.e. hour and weekday classification, respectively) have to be dropped, a more robust assessment might prove to be conclusive. Assessing model performance using a meta variable: In order to further investigate contributing factors to model quality, several approaches featuring a new binary meta target variable, which is derived from the confusion matrices of the existing model results, could be tested. Multiple definitions of how to derive such a metavariable are possible. Machine learning models for binary classification could again be trained to assess variable importance for this new meta model. Balanced bagging: Following the line of Wallace et al. (2011), bagging an ensemble of classifiers induced over balanced bootstrap training samples and predicting the outcome state by using a majority vote could be a valuable approach to obtain more robust results. Correlation issues: Further insights might be gained by considering collinearity in variables and (spatio-temporal) autocorrelation effects. Unobserved heterogeneity: Since it is impossible to include all the data that could potentially determine the likelihood of a traffic accident into a statistical model, future work might focus on model formulations accounting for unobserved heterogeneity (Mannering, 2018). Knowledge-extraction and expert assessment: Tools

for further assessment of black-box models, including – among others – Local Interpretable Model-Agnostic Explanations [LIME, Ribeiro et al. (2016)] and Descriptive mACHINE Learning EXplanations [DALEX, Biecek (2018)] could be used for an in-depth assessment of model quality. In addition, the case-specific random forests (Xu et al., 2016), which are tailored to specific points of interest in the regressor space, could be employed to specifically assess certain road sections of interest. In addition, a comparison with similar analysis conducted in other countries might provide substantial further insights into the applicability of the proposed methodology. Overall, we hope that our findings will contribute to opening up new methodological applications of statistical learning methods in the field of road safety research.

doi:<https://doi.org/10.1016/j.aap.2019.02.008>. <https://www.sciencedirect.com/science/article/pii/S0001457518307760>.

#### **Brad’s Notes:** Statistical Learning

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Schwarz, Felix, and Wolfgang Fastenmeier. “Augmented reality warnings in vehicles: Effects of modality and specificity on effectiveness.” *Accident Analysis & Prevention* 101 (2017): 55–66. doi:<https://doi.org/10.1016/j.aap.2017.01.019>. <https://www.sciencedirect.com/science/article/pii/S0001457517300465>.

#### **Brad’s Notes:** Too Old

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Shangguan, Qiangqiang, Ting Fu, Junhua Wang, Tianyang Luo, and Shou’en Fang. “An integrated methodology for real-time driving risk status prediction using naturalistic driving data.” *Accident Analysis & Prevention* 156 (2021): 106122.

**Suggestions for Future Research:** However, this study still has some limitations. The driving risk prediction method adopted in this paper only focuses on the car-following process, and it is not enough to explore the driving risk during lanechanging or overtaking process. For future work, high-risk lane-changing events and overtaking events will be collected through NDS or actual vehicle test to further improve and validate the accuracy of the proposed driving risk prediction model. In addition, some deep learning algorithms, such as recurrent neural

network, can be applied and compared with the prediction models proposed in this research. Meanwhile, other driving risk influencing factors including vehicle characteristics and road geometry characteristics can be obtained and added to the input variables to further improve the performance of the prediction model. For practical applications, the model will be further applied in the smart vehicle industry fed with real-time naturalistic driving data collected by, for example, ADAS.

doi:<https://doi.org/10.1016/j.aap.2021.106122>. <https://www.sciencedirect.com/science/article/pii/S0001457521001536>.

**Brad's Notes:** Real-time driving risk analysis

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Shi, X., Y.D. Wong, M.Z.F. Li, and C. Chai. "Key risk indicators for accident assessment conditioned on pre-crash vehicle trajectory." *Accident Analysis & Prevention* 117 (2018): 346–356. doi:<https://doi.org/10.1016/j.aap.2018.05.007>. <https://www.sciencedirect.com/science/article/pii/S000145751830191X>.

**Brad's Notes:** Too Old

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Shi, Xiupeng, Yiik Diew Wong, Michael Zhi-Feng Li, Chandrasekar Palanisamy, and Chen Chai. "A feature learning approach based on XGBoost for driving assessment and risk prediction." *Accident Analysis & Prevention* 129 (2019): 170–179.

**Suggestions for Future Research:** None

, doi:<https://doi.org/10.1016/j.aap.2019.05.005>. <https://www.sciencedirect.com/science/article/pii/S0001457518310820>.

**Brad's Notes:** Interesting for focus on ML, Not our dataset, but we could use it.

Shirani-bidabadi, Niloufar, Naveen Mallipaddi, Kirolos Haleem, and Michael Anderson. "Developing Bicycle-Vehicle Crash-Specific Safety Performance Functions in Alabama Using Different Techniques." *Accident Analysis & Prevention* 146 (2020): 105735.

**Suggestions for Future Research:** Further research could compare the findings of this study with other bicycle safety studies in other states to see how bicycle-vehicle crash predictions using the MARS technique would concur or differ. The comparison can also pinpoint any differences in the significant predictors of bicycle-vehicle crashes at both segments and intersections in the analyzed states. Another research venue is to compare the MARS technique with other modeling approaches, e.g., the random-parameter negative binomial model to see how close or far the predictions are.

doi:<https://doi.org/10.1016/j.aap.2020.105735>. <https://www.sciencedirect.com/science/article/pii/S0001457520310149>.

**Brad's Notes:** Small data set. Homework assignment

Shirazi, Mohammadali, Soma Sekhar Dhavala, Dominique Lord, and Srinivas Reddy Geedipally. "A methodology to design heuristics for model selection based on the characteristics of data: Application to investigate when the Negative Binomial Lindley (NB-L) is preferred over the Negative Binomial (NB)." *Accident Analysis & Prevention* 107 (2017): 186–194.

**Suggestions for Future Research:** None

, doi:<https://doi.org/10.1016/j.aap.2017.07.002>. <https://www.sciencedirect.com/science/article/pii/S0001457517302373>.

**Brad's Notes:** Too Old. Not really related to accident analysis. More theoretical. Maybe interesting.

Siebert, Felix Wilhelm, and Hanhe Lin. "Detecting motorcycle helmet use with deep learning." *Accident Analysis & Prevention* 134 (2020): 105319.

**Suggestions for Future Research:** There are a number of limitations to this study. Algorithmic accuracy was only analyzed for road environments within Myanmar, limiting the type of motorcycles and helmets present in the training set. Future studies will need to assess whether the algorithm can maintain the overall high accuracy in road environments in other countries. A similar limitation can be seen in the position of the observation camera. While the algorithm is able to



detect motorcycles from a broad range of angles due to diverse training data, there was no observation site where the observation camera was installed in an overhead position, filming traffic from above. Since traffic surveillance infrastructure is often installed at this position, future studies will need to assess whether the algorithm would produce accurate results from an overhead angle. This is especially important in light of the results of the Yangon II observation site, where an unusual camera angle lead to a large number of missed detections. Furthermore, a more structured variation of camera to lane angle would help to better understand optimal positioning of observation equipment for maximum detection accuracy. While it was included in the data annotation process, the algorithmic accuracy in detecting the position of riders was not compared to human registered data in this study. In light of large differences of motorcycle helmet use for different rider positions (Siebert et al., 2019), future studies will need to incorporate deeper analysis of position detection accuracy. For the comparison of human- and machine-registered helmet use rates, it appears promising to enable a detailed error analysis (false positive/ false negative) through the use of an adapted data structure of human helmet use registration.  
doi:<https://doi.org/10.1016/j.aap.2019.105319>. <https://www.sciencedirect.com/science/article/pii/S0001457519308401>.

**Brad’s Notes:** Not our data. Video data.

Silva, Thiago Christiano, Marcela T. Laiz, and Benjamin Miranda Tabak. “Traffic campaigns and overconfidence: An experimental approach.” *Accident Analysis & Prevention* 146 (2020): 105694. doi:<https://doi.org/10.1016/j.aap.2020.105694>. <https://www.sciencedirect.com/science/article/pii/S0001457519307213>.

Singh, Gyanendra, S.N. Sachdeva, and Mahesh Pal. “M5 model tree based predictive modeling of road accidents on non-urban sections of highways in India.” *Accident Analysis & Prevention* 96 (2016): 108–117. doi:<https://doi.org/10.1016/j.aap.2016.08.004>. <https://www.sciencedirect.com/science/article/pii/S0001457516302822>.

**Brad’s Notes:** Too Old

Smith, Karl U., Henry S.R. Kao, and Richard Kaplan. "Human factors analysis of driver behavior by experimental systems methods." *Accident Analysis & Prevention* 2, no. 1 (1970): 11–20. doi:[https://doi.org/10.1016/0001-4575\(70\)90003-5](https://doi.org/10.1016/0001-4575(70)90003-5). <https://www.sciencedirect.com/science/article/pii/0001457570900035>.

**Brad's Notes:** Too Old

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Smith, Peter M., Ron Saunders, Marni Lifshen, Ollie Black, Morgan Lay, F. Curtis Breslin, Anthony D. LaMontagne, and Emile Tompa. "The development of a conceptual model and self-reported measure of occupational health and safety vulnerability." *Accident Analysis & Prevention* 82 (2015): 234–243. doi:<https://doi.org/10.1016/j.aap.2015.06.004>. <https://www.sciencedirect.com/science/article/pii/S0001457515002286>.

**Brad's Notes:** Too Old

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Smits, Esther, Charlotte Brakenridge, Elise Gane, Jacelle Warren, Michelle Heron-Delaney, Justin Kenardy, and Venerina Johnston. "Identifying risk of poor physical and mental health recovery following a road traffic crash: An industry-specific screening tool." *Accident Analysis & Prevention* 132 (2019): 105280. doi:<https://doi.org/10.1016/j.aap.2019.105280>. <https://www.sciencedirect.com/science/article/pii/S000145751930497X>.

**Brad's Notes:** Not our data, Not ML

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Sohrabi, Soheil, Ali Khodadadi, Seyedeh Maryam Mousavi, Bahar Dadashova, and Dominique Lord. "Quantifying the automated vehicle safety performance: A scoping review of the literature, evaluation of methods, and directions for future research." *Accident Analysis & Prevention* 152 (2021): 106003. doi:<https://doi.org/10.1016/j.aap.2021.106003>. <https://www.sciencedirect.com/science/article/pii/S0001457521000348>.

**Brad's Notes:** Not our data, not ML

Soilán, Mario, Belén Riveiro, Ana Sánchez-Rodríguez, and Pedro Arias. "Safety assessment on pedestrian crossing environments using MLS data." *Accident Analysis & Prevention* 111 (2018): 328–337. doi:<https://doi.org/10.1016/j.aap.2017.12.009>. <https://www.sciencedirect.com/science/article/pii/S0001457517304475>.

**Brad's Notes:** Too Old

Soleimani, Samira, Michael Leitner, and Julius Codjoe. "Applying machine learning, text mining, and spatial analysis techniques to develop a highway-railroad grade crossing consolidation model." *Accident Analysis & Prevention* 152 (2021): 105985.

**Suggestions for Future Research:** For future studies, it may be worth exploring adding up the records of several adjoining cities or parishes to develop a consolidation model for a larger area with more data. However, acquiring spatial attributes for a bigger geographic area may itself present another challenge. Secondly, the quality of FRA data along with its temporal and seasonal effect needs to be further improved. doi:<https://doi.org/10.1016/j.aap.2021.105985>. <https://www.sciencedirect.com/science/article/pii/S0001457521000166>.

**Brad's Notes:** Interesting. Continuation of previous paper.

Soleimani, Samira, Saleh R. Mousa, Julius Codjoe, and Michael Leitner. "A Comprehensive Railroad-Highway Grade Crossing Consolidation Model: A Machine Learning Approach." *Accident Analysis & Prevention* 128 (2019): 65–77.

**Suggestions for Future Research:** None  
, doi:<https://doi.org/10.1016/j.aap.2019.04.002>. <https://www.sciencedirect.com/science/article/pii/S0001457518305736>.

**Brad's Notes:** Interesting. Thorough analysis.

Song, Li, and Wei Fan. “Combined latent class and partial proportional odds model approach to exploring the heterogeneities in truck-involved severities at cross and T-intersections.” *Accident Analysis & Prevention* 144 (2020): 105638.

**Suggestions for Future Research:** In summary, future research could explore the cause of the heterogeneities within variables and between classes, and study the correlation between different factors, as well as include external data for a better understanding of the impact and the transferability of the factors.

doi:<https://doi.org/10.1016/j.aap.2020.105638>. <https://www.sciencedirect.com/science/article/pii/S000145752030289X>.

**Brad’s Notes:** Not ML

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Song, Xiaolin, Yangang Yin, Haotian Cao, Song Zhao, Mingjun Li, and Binlin Yi. “The mediating effect of driver characteristics on risky driving behaviors moderated by gender, and the classification model of driver’s driving risk.” *Accident Analysis & Prevention* 153 (2021): 106038. doi:<https://doi.org/10.1016/j.aap.2021.106038>. <https://www.sciencedirect.com/science/article/pii/S0001457521000695>.

Sonnleitner, Andreas, Matthias Sebastian Treder, Michael Simon, Sven Willmann, Arne Ewald, Axel Buchner, and Michael Schrauf. “EEG alpha spindles and prolonged brake reaction times during auditory distraction in an on-road driving study.” *Accident Analysis & Prevention* 62 (2014): 110–118. doi:<https://doi.org/10.1016/j.aap.2013.08.026>. <https://www.sciencedirect.com/science/article/pii/S0001457513003540>.

**Brad’s Notes:** Too Old

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Sportillo, Daniele, Alexis Paljic, and Luciano Ojeda. “Get ready for automated driving using Virtual Reality.” *Accident Analysis & Prevention* 118 (2018): 102–113. doi:<https://doi.org/10.1016/j.aap.2018.06.003>. <https://www.sciencedirect.com/science/article/pii/S0001457518302197>.

### Brad's Notes: Too Old

Stahl, Patrick, Birsén Donmez, and Greg A. Jamieson. "Supporting anticipation in driving through attentional and interpretational in-vehicle displays." *Accident Analysis & Prevention* 91 (2016): 103–113. doi:<https://doi.org/10.1016/j.aap.2016.02.030>. <https://www.sciencedirect.com/science/article/pii/S000145751630063X>.

### Brad's Notes: Too Old

Suarez-del Fuego, Rocio, Mirko Junge, Francisco Lopez-Valdes, H. Clay Gabler, Lucas Woerner, and Stefan Hiermaier. "Cluster analysis of seriously injured occupants in motor vehicle crashes." *Accident Analysis & Prevention* 151 (2021): 105787.

**Suggestions for Future Research:** The use of the reconstruction delta-v in NASS-CDS is a limitation of this study. Also the assumption of 10,000 kg as the weight of the rigid objects for the calculation of the mass ratio in the cluster analysis has to be considered as a limitation. This assumption produces outliers in the distribution of the MR variable (Fig. 1). The cases considered in this study were not weighted with the NASS-CDS weights. This research focuses on the injury patterns of seriously injured occupants and the collision configurations in which they were involved. Since this study makes no comparison to lower severity crashes, the use of the NASS-CDS weighting factors is not necessary. However, it might be interesting for further research to estimate the contribution of the clusters to the total number of seriously injured occupants in the US. It is important to note that the clusters found in this study contain a large amount of information and research possibilities. The aim of this publication is to present the methodology and to provide insight into the current issues in severe real-world crashes without limiting the impact direction. Further work is planned on the validation of the clusters with a different accident database. Specific injuries and injury mechanisms related to the clusters are currently being investigated.

doi:<https://doi.org/10.1016/j.aap.2020.105787>. <https://www.sciencedirect.com/science/article/pii/S0001457520316079>.

**Brad's Notes:** Not our data set, Unsupervised Clustering, Interesting for clustering algorithm and suggestions for future work.

Svenson, Ola. "Risks of road transportation in a psychological perspective." *Accident Analysis & Prevention* 10, no. 4 (1978): 267–280. doi:[https://doi.org/10.1016/0001-4575\(78\)90029-5](https://doi.org/10.1016/0001-4575(78)90029-5). <https://www.sciencedirect.com/science/article/pii/0001457578900295>.

**Brad's Notes:** Too Old

Tamakloe, Reuben, Jungyeol Hong, and Dongjoo Park. "A copula-based approach for jointly modeling crash severity and number of vehicles involved in express bus crashes on expressways considering temporal stability of data." *Accident Analysis & Prevention* 146 (2020): 105736.

**Suggestions for Future Research:** In the future, it would be interesting to identify which subsets of crash populations that show temporal stability/instability. It would also be worthwhile to employ machine learning algorithms to identify important rules that show a set of factors leading to bus-involved crashes, especially at mainline sections where crashes are usually severe.  
doi:<https://doi.org/10.1016/j.aap.2020.105736>. <https://www.sciencedirect.com/science/article/pii/S0001457520309994>.

**Brad's Notes:** Not ML

Tan, Yaoyuan V., Michael R. Elliott, and Carol A.C. Flannagan. "Development of a real-time prediction model of driver behavior at intersections using kinematic time series data." *Accident Analysis & Prevention* 106 (2017): 428–436. doi:<https://doi.org/10.1016/j.aap.2017.07.003>. <https://www.sciencedirect.com/science/article/pii/S0001457517302385>.

**Brad's Notes:** Too Old

Tang, Dongjie, Xiaohan Yang, and Xuesong Wang. “Improving the transferability of the crash prediction model using the TrAdaBoost.R2 algorithm.” *Accident Analysis & Prevention* 141 (2020): 105551. doi:<https://doi.org/10.1016/j.aap.2020.105551>. <https://www.sciencedirect.com/science/article/pii/S0001457519317166>.

**Brad’s Notes:** Interesting. Calibrating the transfer of a model built for one data set to

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Tang, Jinjun, Jian Liang, Chunyang Han, Zhibin Li, and Helai Huang. “Crash injury severity analysis using a two-layer Stacking framework.” *Accident Analysis & Prevention* 122 (2019): 226–238.

**Suggestions for Future Research:** Further research can focus on selecting more reasonable hyper parameters to improve the performance of the model. In addition, a future research direction could be how to consider the spatial-temporal correlations in the modeling structure between crash severity and explanatory factors. doi:<https://doi.org/10.1016/j.aap.2018.10.016>. <https://www.sciencedirect.com/science/article/pii/S0001457518308546>.

**Brad’s Notes:** Interesting. Uses multiple methods, mixing ML and Statistics.

Tarko, Andrew P. “Analyzing road near departures as failure-caused events.” *Accident Analysis & Prevention* 142 (2020): 105536.

**Suggestions for Future Research:** More studies are needed to build further confidence towards the proposed failure-based traffic conflicts method. One of the available opportunities is provided by naturalistic driving studies that deliver traffic conflicts and collisions for the same observation period. The already mentioned opportunity provided by emerging autonomous vehicles is quite a realistic expectation which emphasizes the importance of collecting and sharing such data for improving safety on public roads with presence of new generation vehicles. doi:<https://doi.org/10.1016/j.aap.2020.105536>. <https://www.sciencedirect.com/science/article/pii/S0001457519312680>.

**Brad's Notes:** Not ML. Not applicable to our data.

Taylor, Jennifer A., Alicia V. Lacovara, Gordon S. Smith, Ravi Pandian, and Mark Lehto. "Near-miss narratives from the fire service: A Bayesian analysis." *Accident Analysis & Prevention* 62 (2014): 119–129. doi:<https://doi.org/10.1016/j.aap.2013.09.012>. <https://www.sciencedirect.com/science/article/pii/S0001457513003655>.

**Brad's Notes:** Too Old

Thapa, Diwas, and Sabyasachee Mishra. "Using worker's naturalistic response to determine and analyze work zone crashes in the presence of work zone intrusion alert systems." *Accident Analysis & Prevention* 156 (2021): 106125. doi:<https://doi.org/10.1016/j.aap.2021.106125>. <https://www.sciencedirect.com/science/article/pii/S0001457521001561>.

Tselentis, Dimitrios I., Eleni I. Vlahogianni, and George Yannis. "Temporal analysis of driving efficiency using smartphone data." *Accident Analysis & Prevention* 154 (2021): 106081. doi:<https://doi.org/10.1016/j.aap.2021.106081>. <https://www.sciencedirect.com/science/article/pii/S0001457521001123>.

Ulak, Mehmet Baran, Eren Erman Ozguven, Omer Arda Vanli, Maxim A. Dulebenets, and Lisa Spainhour. "Multivariate random parameter Tobit modeling of crashes involving aging drivers, passengers, bicyclists, and pedestrians: Spatiotemporal variations." *Accident Analysis & Prevention* 121 (2018): 1–13. doi:<https://doi.org/10.1016/j.aap.2018.08.031>. <https://www.sciencedirect.com/science/article/pii/S0001457518305566>.

**Brad's Notes:** Too Old

Vallmuur, Kirsten. "Machine learning approaches to analysing textual injury surveillance data: A systematic review." *Accident Analysis & Prevention* 79 (2015): 41–49. doi:<https://doi.org/10.1016/j.aap.2015.03.018>. <https://www.sciencedirect.com/science/article/pii/S0001457515000925>.



**Brad’s Notes:** Too Old

van der Wall, H.E.C., R.J. Doll, G.J.P. van Westen, I. Koopmans, R.G. Zuiker, J. Burggraaf, and A.F. Cohen. “The use of machine learning improves the assessment of drug-induced driving behaviour.” *Accident Analysis & Prevention* 148 (2020): 105822. doi:<https://doi.org/10.1016/j.aap.2020.105822>. <https://www.sciencedirect.com/science/article/pii/S0001457520316420>.

Wali, Behram, Asad J. Khattak, and Numan Ahmad. “Injury severity analysis of pedestrian and bicyclist trespassing crashes at non-crossings: A hybrid predictive text analytics and heterogeneity-based statistical modeling approach.” *Accident Analysis & Prevention* 150 (2021): 105835.

**Suggestions for Future Research:** Thus, in future, with the availability of more crash narrative data, the methodology in this study can be expanded to account for potential temporal heterogeneity – allowing even better interpretation of crash narrative data-analysis findings. doi:<https://doi.org/10.1016/j.aap.2020.105835>. <https://www.sciencedirect.com/science/article/pii/S0001457520316559>.

**Brad’s Notes:** Not our data. Text analytics of crash narratives. Railroad crossings.

Wali, Behram, Asad J. Khattak, and Thomas Karnowski. “Exploring microscopic driving volatility in naturalistic driving environment prior to involvement in safety critical events—Concept of event-based driving volatility.” *Accident Analysis & Prevention* 132 (2019): 105277. doi:<https://doi.org/10.1016/j.aap.2019.105277>. <https://www.sciencedirect.com/science/article/pii/S0001457519312369>.

**Brad’s Notes:** Not our data.

Walker, Guy H., Neville A. Stanton, and Paul M. Salmon. “Cognitive compatibility of motorcyclists and car drivers.” *Accident Analysis & Prevention* 43, no. 3 (2011): 878–888. doi:<https://doi.org/10.1016/j.aap.2010.11.008>. <https://www.sciencedirect.com/science/article/pii/S0001457510003386>.

**Brad's Notes: Too Old**

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Waller, Patrica. "Perilous progress. Management the hazards of technology: R.W. Kates, C. Hohenemser and J. X. Kasperson, eds. Westview Press, Boulder CO, U.S.A., 1985. 489 pp. \$33.50. ISBN 0-8133-7025-6." *Accident Analysis & Prevention* 20, no. 6 (1988): 465–467. doi:[https://doi.org/10.1016/0001-4575\(88\)90045-0](https://doi.org/10.1016/0001-4575(88)90045-0). <https://www.sciencedirect.com/science/article/pii/0001457588900450>.

**Brad's Notes: Too Old**

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Wang, Chen, Chengcheng Xu, and Yulu Dai. "A crash prediction method based on bivariate extreme value theory and video-based vehicle trajectory data." *Accident Analysis & Prevention* 123 (2019): 365–373. doi:<https://doi.org/10.1016/j.aap.2018.12.013>. <https://www.sciencedirect.com/science/article/pii/S0001457518304275>.

**Brad's Notes: Not ML**

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Wang, Jianqiang, Yang Zheng, Xiaofei Li, Chenfei Yu, Kenji Kodaka, and Keqiang Li. "Driving risk assessment using near-crash database through data mining of tree-based model." *Accident Analysis & Prevention* 84 (2015): 54–64. doi:<https://doi.org/10.1016/j.aap.2015.07.007>. <https://www.sciencedirect.com/science/article/pii/S0001457515300129>.

**Brad's Notes: Too Old**

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Wang, Junhua, Yumeng Kong, and Ting Fu. "Expressway crash risk prediction using back propagation neural network: A brief investigation on safety resilience." *Accident Analysis & Prevention* 124 (2019): 180–192.

**Suggestions for Future Research:** However, limitations exist in this study and should be further included in future studies. Without traffic data collected from the road section used in the simulation, we were not able to fully calibrate the simulation. Though the use of the virtual and simplified simulation scenario is able to serve the purpose of the study in illustrating the model and the concept of traffic resilience, the simulation should be better calibrated and the model should be further trained and validated using traffic data from real road environments with the help of new technologies such as computer vision and LiDAR techniques (Atev et al., 2005; St-Aubin et al., 2015; Tarko et al., 2017). Slow moving vehicles with different speeds may have different impacts on freeway safety, but such impacts have not been extensively investigated in this study. A sensitivity analysis for different speeds of slow moving vehicles can be performed using the simulation software. In addition, environments with other types of moving violations will be further investigated with developments in simulation tools. Despite rear-end collisions are the most common type of crashes on expressways, other collision types need to be considered in future work. As being promising in crash prediction, the approach using machine learning techniques in crash risk analysis will be further explored with different advanced machine learning methods applied and tested. The safety resilience of traffic will be deeper explored both theoretically and practically. Finding proper methods to quantify and identify indicators to explain the safety resilience can be an interesting topic to study.  
doi:<https://doi.org/10.1016/j.aap.2019.01.007>. <https://www.sciencedirect.com/science/article/pii/S0001457519300302>.

**Brad’s Notes:** Not our data. Simulation

Wang, Junhua, Boya Liu, Ting Fu, Shuo Liu, and Joshua Stipancic. “Modeling when and where a secondary accident occurs.” Road Safety Data Considerations, *Accident Analysis & Prevention* 130 (2019): 160–166. doi:<https://doi.org/10.1016/j.aap.2018.01.024>. <https://www.sciencedirect.com/science/article/pii/S0001457518300307>.

**Brad’s Notes:** Not our data, but interesting.

Takes into account crash severity, violation category, weather conditions, tow away, road surface conditions, lighting, parties involved (?), traffic volume, duration, and shock wave speed (?).

Got "accident data and traffic loop data collected over three years from California interstate freeways," but none of them are from California. Data is 2010-2012, even though the paper is from 2019. (?) Doesn't say where they got the weather report, unless it's in the SWITRS records.

Wang, Junhua, Tianyang Luo, and Ting Fu. "Crash prediction based on traffic platoon characteristics using floating car trajectory data and the machine learning approach." *Accident Analysis & Prevention* 133 (2019): 105320.

**Suggestions for Future Research:** For future work, the models will be tested and improved with data from a large number of expressway environments. Crash prediction at expressway ramps should be further explored using different methods. Other urban road environments should also be investigated. Real-time crash prediction using live floating car data will also be tested.

doi:<https://doi.org/10.1016/j.aap.2019.105320>. <https://www.sciencedirect.com/science/article/pii/S0001457519307468>.

**Brad's Notes:** Not our data. Traffic platoon is the group of vehicles the crash vehicle belongs to before the crash.

Wang, Junhua, Shuaiyi Sun, Shouen Fang, Ting Fu, and Joshua Stipanovic. "Predicting drowsy driving in real-time situations: Using an advanced driving simulator, accelerated failure time model, and virtual location-based services." *Accident Analysis & Prevention* 99 (2017): 321–329. doi:<https://doi.org/10.1016/j.aap.2016.12.014>. <https://www.sciencedirect.com/science/article/pii/S0001457516304523>.

**Brad's Notes:** Too Old

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Wang, Qingfan, Shun Gan, Wentao Chen, Quan Li, and Bingbing Nie. “A data-driven, kinematic feature-based, near real-time algorithm for injury severity prediction of vehicle occupants.” *Accident Analysis & Prevention* 156 (2021): 106149.

**Suggestions for Future Research:** None  
, doi:<https://doi.org/10.1016/j.aap.2021.106149>. <https://www.sciencedirect.com/science/article/pii/S0001457521001809>.

**Brad’s Notes:** Interesting. Numerical database of simulations.

Wang, Song, and Zhixia Li. “Exploring causes and effects of automated vehicle disengagement using statistical modeling and classification tree based on field test data.” *Accident Analysis & Prevention* 129 (2019): 44–54. doi:<https://doi.org/10.1016/j.aap.2019.04.015>. <https://www.sciencedirect.com/science/article/pii/S0001457519300016>.

**Brad’s Notes:** Not our data.

Watling, Christopher N., Md Mahmudul Hasan, and Grégoire S. Larue. “Sensitivity and specificity of the driver sleepiness detection methods using physiological signals: A systematic review.” *Accident Analysis & Prevention* 150 (2021): 105900. doi:<https://doi.org/10.1016/j.aap.2020.105900>. <https://www.sciencedirect.com/science/article/pii/S0001457520317206>.

Wei, Yanning, Keping Li, and Keshuang Tang. “Trajectory-based identification of critical instantaneous decision events at mixed-flow signalized intersections.” *Accident Analysis & Prevention* 123 (2019): 324–335. doi:<https://doi.org/10.1016/j.aap.2018.11.019>. <https://www.sciencedirect.com/science/article/pii/S0001457518303968>.

Wellman, Helen M, Mark R Lehto, Gary S Sorock, and Gordon S Smith. “Computerized coding of injury narrative data from the National Health Interview Survey.” *Accident Analysis & Prevention* 36, no. 2 (2004): 165–171. doi:[https://doi.org/10.1016/S0001-4575\(02\)00146-X](https://doi.org/10.1016/S0001-4575(02)00146-X). <https://www.sciencedirect.com/science/article/pii/S000145750200146X>.

**Brad's Notes: Too Old**

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Wen, Huiying, Xuan Zhang, Qiang Zeng, and N.N. Sze. "Bayesian spatial-temporal model for the main and interaction effects of roadway and weather characteristics on freeway crash incidence." *Accident Analysis & Prevention* 132 (2019): 105249.

**Suggestions for Future Research:** Yet, the effects of only two roadway factors on the freeway crash risk are explored in current study. It would be worth exploring the effects of other geometric design characteristics, e.g., number of lanes, lane width, and shoulder width, and their interactions with the weather conditions, on the crash risk, when the comprehensive traffic and crash data of a bigger freeway network are available in the extended study. Methodological-wise, it is a common approach to examine the interaction effects on the association by adding the corresponding interaction terms into the link function of regression. Yet, it is worth exploring the viability of other alternate approaches, e.g., machine learning techniques (Zeng et al., 2016), to reveal the interaction effects when more comprehensive traffic, driver and weather data are available in future study. Additionally, a random-parameter model can be set out to capture the heterogeneous effects of the observed factors on the association (Mannering et al., 2016).  
doi:<https://doi.org/10.1016/j.aap.2019.07.025>. <https://www.sciencedirect.com/science/article/pii/S0001457519304117>.

**Brad's Notes: Not ML**

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Wilde, Gerald J.S. "Beyond the concept of risk homeostatis: Suggestions for research and application towards the prevention of accidents and lifestyle-related disease." *Accident Analysis & Prevention* 18, no. 5 (1986): 377–401. doi:[https://doi.org/10.1016/0001-4575\(86\)90012-6](https://doi.org/10.1016/0001-4575(86)90012-6).  
<https://www.sciencedirect.com/science/article/pii/0001457586900126>.

**Brad's Notes: Too Old**

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Williamson, Ann, David A. Lombardi, Simon Folkard, Jane Stutts, Theodore K. Courtney, and Jennie L. Connor. “The link between fatigue and safety.” *Advancing Fatigue and Safety Research, Accident Analysis & Prevention* 43, no. 2 (2011): 498–515. doi:<https://doi.org/10.1016/j.aap.2009.11.011>. <https://www.sciencedirect.com/science/article/pii/S0001457509003121>.

**Brad’s Notes: Too Old**

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Winkler, Susann, Juela Kazazi, and Mark Vollrath. “How to warn drivers in various safety-critical situations – Different strategies, different reactions.” *Accident Analysis & Prevention* 117 (2018): 410–426. doi:<https://doi.org/10.1016/j.aap.2018.01.040>. <https://www.sciencedirect.com/science/article/pii/S0001457518300472>.

**Brad’s Notes: Too Old**

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———. “Practice makes better – Learning effects of driving with a multi-stage collision warning.” *Accident Analysis & Prevention* 117 (2018): 398–409. doi:<https://doi.org/10.1016/j.aap.2018.01.018>. <https://www.sciencedirect.com/science/article/pii/S0001457518300186>.

**Brad’s Notes: Too Old**

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Wörle, Johanna, Barbara Metz, and Martin Baumann. “Sleep inertia in automated driving: Post-sleep take-over and driving performance.” *Accident Analysis & Prevention* 150 (2021): 105918. doi:<https://doi.org/10.1016/j.aap.2020.105918>. <https://www.sciencedirect.com/science/article/pii/S0001457520317383>.

Wörle, Johanna, Barbara Metz, Ina Othersen, and Martin Baumann. “Sleep in highly automated driving: Takeover performance after waking up.” *Accident Analysis & Prevention* 144 (2020): 105617. doi:<https://doi.org/10.1016/j.aap.2020.105617>. <https://www.sciencedirect.com/science/article/pii/S0001457519313478>.

Wu, Yuan-Wei, and Tien-Pen Hsu. “Mid-term prediction of at-fault crash driver frequency using fusion deep learning with city-level traffic violation data.” *Accident Analysis & Prevention* 150 (2021): 105910. doi:<https://doi.org/10.1016/j.aap.2020.105910>. <https://www.sciencedirect.com/science/article/pii/S0001457520317309>.

**Brad’s Notes:** Not our data. Correlations between traffic violations and crashes.

Xing, Lu, Jie He, Ye Li, Yina Wu, Jinghui Yuan, and Xin Gu. “Comparison of different models for evaluating vehicle collision risks at upstream diverging area of toll plaza.” *Accident Analysis & Prevention* 135 (2020): 105343. doi:<https://doi.org/10.1016/j.aap.2019.105343>. <https://www.sciencedirect.com/science/article/pii/S0001457519307584>.

**Brad’s Notes:** Not our data, Automated analysis of video from drones

Xiong, Xiaoxia, Meng Wang, Yingfeng Cai, Long Chen, Haneen Farah, and Marjan Hagenzieker. “A forward collision avoidance algorithm based on driver braking behavior.” *Accident Analysis & Prevention* 129 (2019): 30–43.

**Suggestions for Future Research:** The proposed framework provides a new perspective on real-time risk level classification and collision avoidance system development. However, since there is a limitation in data sample size representing critical event-reaction braking, more deceleration profiles (by collecting more near-crash records from other resources) should be explored to improve parameter tuning of the proposed fuzzy logic in the future (especially obtaining more higher-speed observations to overcome the current limitation in the algorithm for higher-speed braking scenarios). Besides, traffic/ driver/vehicle characteristics (such as vehicle type, driver state, and vehicle response during braking, etc.) need to be investigated in future research concerning their possible effects on timing of critical braking. Also, variations of safety indicators representing uncertain critical driving scenarios could be further considered, and the probability of the uncertain scenarios could



also be explored (by predicting accelerating/ decelerating behaviors of SV and POV in V2V environments) and introduced into the fuzzy logic (by assigning probability-based weights of fuzzy rules) to improve its risk level classification performance. In addition, other machine learning classification algorithms (such as Support Vector Machine) instead of fuzzy logic could be explored to learn the effective representation of risk levels derived from offline deceleration profiles in further study.  
doi:<https://doi.org/10.1016/j.aap.2019.05.004>. <https://www.sciencedirect.com/science/article/pii/S0001457519300703>.

**Brad’s Notes:** Not ML. Interesting for (claim of) being new approach.

Xu, Chengcheng, Pan Liu, Wei Wang, and Zhibin Li. “Safety performance of traffic phases and phase transitions in three phase traffic theory.” *Accident Analysis & Prevention* 85 (2015): 45–57. doi:<https://doi.org/10.1016/j.aap.2015.08.018>. <https://www.sciencedirect.com/science/article/pii/S0001457515300518>.

**Brad’s Notes:** Too Old

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Xu, Chengcheng, Wei Wang, Pan Liu, and Zhibin Li. “Calibration of crash risk models on freeways with limited real-time traffic data using Bayesian meta-analysis and Bayesian inference approach.” *Accident Analysis & Prevention* 85 (2015): 207–218. doi:<https://doi.org/10.1016/j.aap.2015.09.016>. <https://www.sciencedirect.com/science/article/pii/S0001457515300737>.

**Brad’s Notes:** Too Old

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Yahaya, Mahama, Runhua Guo, Wenbo Fan, Kamal Bashir, Yingfei Fan, Shiwei Xu, and Xinguo Jiang. “Bayesian networks for imbalance data to investigate the contributing factors to fatal injury crashes on the Ghanaian highways.” *Accident Analysis & Prevention* 150 (2021): 105936. doi:<https://doi.org/10.1016/j.aap.2020.105936>. <https://www.sciencedirect.com/science/article/pii/S0001457520317565>.

**Brad's Notes:** See same article by same authors.

Yahaya, Mahama, Runhua Guo, Xinguo Jiang, Kamal Bashir, Caroline Matara, and Shiwei Xu. "Ensemble-based model selection for imbalanced data to investigate the contributing factors to multiple fatality road crashes in Ghana." *Accident Analysis & Prevention* 151 (2021): 105851.

**Suggestions for Future Research:** Our future work will devise a framework to simultaneously handle crash data imbalance and noise, since their presence is counterproductive for prediction and data analysis (Drummond and Holte, 2005; Saez et al., 2015).

doi:<https://doi.org/10.1016/j.aap.2020.105851>. <https://www.sciencedirect.com/science/article/pii/S0001457520316717>.

**Brad's Notes:** Not ML. Interesting for different methods for imbalanced data.

Yan, Xintong, Jie He, Changjian Zhang, Ziyang Liu, Boshuai Qiao, and Hao Zhang. "Single-vehicle crash severity outcome prediction and determinant extraction using tree-based and other non-parametric models." *Accident Analysis & Prevention* 153 (2021): 106034. doi:<https://doi.org/10.1016/j.aap.2021.106034>. <https://www.sciencedirect.com/science/article/pii/S0001457521000658>.

Yang, Guangchuan, Mohamed Ahmed, and Eric Adomah. "An Integrated Microsimulation Approach for Safety Performance Assessment of the Wyoming Connected Vehicle Pilot Deployment Program." *Accident Analysis & Prevention* 146 (2020): 105714.

**Suggestions for Future Research:** Future works should also further investigate the safety benefits of the pilot's CV applications under different weather and traffic events, such as a freeway work zone under low visibility condition, and road closure and rerouting due to traffic crashes.

doi:<https://doi.org/10.1016/j.aap.2020.105714>. <https://www.sciencedirect.com/science/article/pii/S0001457520305200>.

**Brad's Notes:** Simulation, Not ML

Yang, Guangchuan, Mohamed Ahmed, Sherif Gaweesh, and Eric Adomah. "Connected vehicle real-time traveler information messages for freeway speed harmonization under adverse weather conditions: Trajectory level analysis using driving simulator." *Accident Analysis & Prevention* 146 (2020): 105707. doi:<https://doi.org/10.1016/j.aap.2020.105707>. <https://www.sciencedirect.com/science/article/pii/S0001457519315738>.

**Brad's Notes:** Not our data, connected vehicles, driving simulator

Yang, Hong, Zhenyu Wang, Kun Xie, Kaan Ozbay, and Marianna Imprialou. "Methodological evolution and frontiers of identifying, modeling and preventing secondary crashes on highways." *Accident Analysis & Prevention* 117 (2018): 40–54. doi:<https://doi.org/10.1016/j.aap.2018.04.001>. <https://www.sciencedirect.com/science/article/pii/S0001457518301398>.

**Brad's Notes:** Too Old

Yang, Huanjia, David A.S. Chew, Weiwei Wu, Zhipeng Zhou, and Qiming Li. "Design and implementation of an identification system in construction site safety for proactive accident prevention." *Intelligent Speed Adaptation + Construction Projects, Accident Analysis & Prevention* 48 (2012): 193–203. doi:<https://doi.org/10.1016/j.aap.2011.06.017>. <https://www.sciencedirect.com/science/article/pii/S0001457511001837>.

**Brad's Notes:** Too Old

Yang, Kui, Rongjie Yu, Xuesong Wang, Mohammed Quddus, and Lifang Xue. "How to determine an optimal threshold to classify real-time crash-prone traffic conditions?" *Accident Analysis & Prevention* 117 (2018): 250–261. doi:<https://doi.org/10.1016/j.aap.2018.04.022>. <https://www.sciencedirect.com/science/article/pii/S0001457518301751>.

**Brad's Notes:** Too Old

Yang, Liu, Wei Guan, Rui Ma, and Xiaomeng Li. "Comparison among driving state prediction models for car-following condition based on EEG and driving features." *Accident Analysis & Prevention* 133 (2019): 105296. doi:<https://doi.org/10.1016/j.aap.2019.105296>. <https://www.sciencedirect.com/science/article/pii/S0001457518306547>.

**Brad's Notes:** Not our data,

Yang, Liu, Rui Ma, H. Michael Zhang, Wei Guan, and Shixiong Jiang. "Driving behavior recognition using EEG data from a simulated car-following experiment." *Simulation of Traffic Safety in the Era of Advances in Technologies, Accident Analysis & Prevention* 116 (2018): 30–40. doi:<https://doi.org/10.1016/j.aap.2017.11.010>. <https://www.sciencedirect.com/science/article/pii/S0001457517303974>.

**Brad's Notes:** Too Old

Young, K.L, S. Koppel, and J.L Charlton. "Toward best practice in Human Machine Interface design for older drivers: A review of current design guidelines." *Accident Analysis & Prevention* 106 (2017): 460–467. doi:<https://doi.org/10.1016/j.aap.2016.06.010>. <https://www.sciencedirect.com/science/article/pii/S0001457516302068>.

**Brad's Notes:** Too Old

Young, William, Amir Sobhani, Michael G. Lenné, and Majid Sarvi. "Simulation of safety: A review of the state of the art in road safety simulation modelling." *Accident Analysis & Prevention* 66 (2014): 89–103. doi:<https://doi.org/10.1016/j.aap.2014.01.008>. <https://www.sciencedirect.com/science/article/pii/S0001457514000128>.

**Brad's Notes:** Too Old

Yu, Rongjie, and Mohamed Abdel-Aty. “Utilizing support vector machine in real-time crash risk evaluation.” *Accident Analysis & Prevention* 51 (2013): 252–259. doi:<https://doi.org/10.1016/j.aap.2012.11.027>. <https://www.sciencedirect.com/science/article/pii/S0001457512004186>.

#### **Brad’s Notes: Too Old**

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Yu, Rongjie, Lei Han, and Hui Zhang. “Trajectory data based freeway high-risk events prediction and its influencing factors analyses.” *Accident Analysis & Prevention* 154 (2021): 106085. doi:<https://doi.org/10.1016/j.aap.2021.106085>. <https://www.sciencedirect.com/science/article/pii/S0001457521001160>.

Yu, Rongjie, Xiaojie Long, Mohammed Quddus, and Junhua Wang. “A Bayesian Tobit quantile regression approach for naturalistic longitudinal driving capability assessment.” *Accident Analysis & Prevention* 147 (2020): 105779. doi:<https://doi.org/10.1016/j.aap.2020.105779>. <https://www.sciencedirect.com/science/article/pii/S0001457520315992>.

#### **Brad’s Notes: Not ML**

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Yu, Rongjie, Yin Zheng, Mohamed Abdel-Aty, and Zhen Gao. “Exploring crash mechanisms with microscopic traffic flow variables: A hybrid approach with latent class logit and path analysis models.” *Accident Analysis & Prevention* 125 (2019): 70–78.

**Suggestions for Future Research:** However, given the interesting findings from the proposed modeling approach, there are still several limitations of the current study. (1) First, this study employed matched case-control data structure with a fixed crash and non-crash ratio (1:4) to deal with the imbalanced crash risk analysis dataset. In future studies, other sampling techniques, such as over-sampling methods of synthetic minority oversampling technique (SMOTE) (Chawla et al., 2002) and full-size data would be tested. And the effects of sampling methods on the concurrent microscopic influencing factors need to be revealed. (2) Second, this study utilized the LCL model to group observations to account for the heterogeneity issues, and future efforts

would be conducted to identify how to improve the proposed hybrid approach from the aspects of incorporating other clustering methods, such as finite mixture model (FMM) (Park and Lord, 2009). (3) Moreover, after applying the LCL model to solve the heterogeneity issues, repeated measures still exist within a latent class. In this study, the matched case-control data preparation process can greatly reduce the impacts of repeated measures on the analysis results. While in future studies, other methods would be tested to solve this repeated measurement issues, such as incorporating the LCL model with roadway section unique random effect terms. (4) In addition, in this study, the PA models were employed to conduct the causal inference, which is a typical mediation analysis method. Additional efforts are needed to utilize other causal inference methods (Pearl, 2018), like propensity score matching (PSM) (Li et al., 2013; Li and Graham, 2016), to further explorations the causal relationships between crash occurrence and the microscopic traffic flow variables.

doi:<https://doi.org/10.1016/j.aap.2019.01.022>. <https://www.sciencedirect.com/science/article/pii/S0001457518307073>.

**Brad's Notes:** Not our data

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Zador, Paul L. "Right-turn-on-red laws and motor vehicle crashes: A review of the literature." *Accident Analysis & Prevention* 16, no. 4 (1984): 241–245. doi:[https://doi.org/10.1016/0001-4575\(84\)90019-8](https://doi.org/10.1016/0001-4575(84)90019-8). <https://www.sciencedirect.com/science/article/pii/0001457584900198>.

**Brad's Notes:** Too Old

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Zafian, Tracy, Alyssa Ryan, Ravi Agrawal, Siby Samuel, and Michael Knodler. "Using SHRP2 NDS data to examine infrastructure and other factors contributing to older driver crashes during left turns at signalized intersections." *Accident Analysis & Prevention* 156 (2021): 106141. doi:<https://doi.org/10.1016/j.aap.2021.106141>. <https://www.sciencedirect.com/science/article/pii/S000145752100172X>.

Zhang, Changjian, Jie He, Mark King, Ziyang Liu, Yikai Chen, Xintong Yan, Lu Xing, and Hao Zhang. “A crash risk identification method for freeway segments with horizontal curvature based on real-time vehicle kinetic response.” *Accident Analysis & Prevention* 150 (2021): 105911.

**Suggestions for Future Research:** More Data  
, doi:<https://doi.org/10.1016/j.aap.2020.105911>. <https://www.sciencedirect.com/science/article/pii/S0001457520317310>.

**Brad’s Notes:** Not ML

Zhang, Junyi, Koji Suto, and Akimasa Fujiwara. “Effects of in-vehicle warning information on drivers’ decelerating and accelerating behaviors near an arch-shaped intersection.” *Accident Analysis & Prevention* 41, no. 5 (2009): 948–958. doi:<https://doi.org/10.1016/j.aap.2009.05.010>. <https://www.sciencedirect.com/science/article/pii/S0001457509001110>.

**Brad’s Notes:** Too Old

Zhang, Shile, Mohamed Abdel-Aty, Qing Cai, Pei Li, and Jorge Ugan. “Prediction of pedestrian-vehicle conflicts at signalized intersections based on long short-term memory neural network.” *Accident Analysis & Prevention* 148 (2020): 105799. doi:<https://doi.org/10.1016/j.aap.2020.105799>. <https://www.sciencedirect.com/science/article/pii/S0001457520316195>.

**Brad’s Notes:** Not our data. Video data. I think this is “detection,” not “prediction.”

Zhang, Shile, Mohamed Abdel-Aty, Yina Wu, and Ou Zheng. “Modeling pedestrians’ near-accident events at signalized intersections using gated recurrent unit (GRU).” *Accident Analysis & Prevention* 148 (2020): 105844. doi:<https://doi.org/10.1016/j.aap.2020.105844>. <https://www.sciencedirect.com/science/article/pii/S000145752031664X>.

**Brad’s Notes:** Gated Recurrent Unit (GRU) is like Long Short-term Memory (LSTM), but a little simpler.  
Used video data of pedestrians at intersections to find near-accident events.  
Not our data.

Zhao, Can, Li Li, Xin Pei, Zhiheng Li, Fei-Yue Wang, and Xiangbin Wu. “A comparative study of state-of-the-art driving strategies for autonomous vehicles.” *Accident Analysis & Prevention* 150 (2021): 105937.

**Suggestions for Future Research:** We believe that future research should focus on the following valuable directions: 1) Limited by the level of hardware and algorithm, there is still much room for improvement in the accuracy and range of the current perception system. Therefore, as the latter segment of perception, the driving strategies of AVs need to be designed specifically based on some limitations and assumptions of perception, and hence cannot solve all problems in a generic way. 2) The current driving strategies are based on an indispensable assumption of using identical technical equipment and the same control strategy for all vehicles (Geiger et al., 2012). However, due to the inconsistency of interpretation models and preferred objectives, different AVs may have different understandings and responses to the same scenarios. When they lack necessary communication or communication channels are disturbed, their misunderstandings and misjudgments will become a new trigger to danger. Therefore, how to formulate a framework to ensure that AVs with different driving strategies still can reach consensus is an urgent issue for future researchers. 3) So far, research on risk appetite, the feature closely related to safety, is still insufficient and deserves further advancement. Especially, how should the risk appetite of different strategies be tested, evaluated, and quantified. In consideration of the long-tail problem, how to design simulation tests to reflect the risk appetite of the strategies accurately (Li et al., 2016, 2018a; Li et al., 2019a,b). 4) Future research should focus more on communication and collaboration between vehicles. For collaboration with other AVs, the unification of communication rules and protocols should be accelerated, to form a standardized and extensible inter-vehicle communication mechanism. 5) For collaboration with human-driven vehicles, we should further construct human driver models from the cognitive level rather than the behaviors itself (Efrati, 2018; Stewart, 2018; Ma



et al., 2010; Schwarting et al., 2019; Li et al., 2018b; Michon, 1985). It can help massively to develop a more reasonable collaborative driving strategy and improve the probability of understanding each other correctly when AVs interact with human-driven vehicles. 6) In the next step, researchers should pay more attention to TPACC and explore the possibility of combining it with collaborative driving. It is a meaningful work to accurately compare the individual benefits and the overall benefits through theoretical calculations or simulation tests. 7) The purpose of this paper is to draw attention of researchers towards these important directions. We expect more exciting results will be obtained soon. doi:<https://doi.org/10.1016/j.aap.2020.105937>. <https://www.sciencedirect.com/science/article/pii/S0001457520317577>.

**Brad's Notes:** Not ML

Zhao, Guozhen, and Changxu Wu. "Effectiveness and acceptance of the intelligent speeding prediction system (ISPS)." *Accident Analysis & Prevention* 52 (2013): 19–28. doi:<https://doi.org/10.1016/j.aap.2012.12.013>. <https://www.sciencedirect.com/science/article/pii/S0001457512004356>.

**Brad's Notes:** Too Old

Zhao, Xiaocong, Ren He, and Jianqiang Wang. "How do drivers respond to driving risk during car-following? Risk-response driver model and its application in human-like longitudinal control." *Accident Analysis & Prevention* 148 (2020): 105783. doi:<https://doi.org/10.1016/j.aap.2020.105783>. <https://www.sciencedirect.com/science/article/pii/S0001457520316031>.

**Brad's Notes:** Not ML. Not our data.

Zhou, Tuqiang, and Junyi Zhang. "Analysis of commercial truck drivers' potentially dangerous driving behaviors based on 11-month digital tachograph data and multilevel modeling approach." *Accident Analysis & Prevention* 132 (2019): 105256.

**Suggestions for Future Research:** The paper proposes an innovative approach to extracting useful information about commercial truck driver behavior from widely available big data sources. This study used eleven months of digital tachograph data that comprised 4373 trips made by 70 truck drivers in Japan. Results suggest that 40% of truck drivers exhibit substantially dangerous driving tendencies. The explanatory variables introduced in this study accurately expressed the influence of unobserved conditions and phenomena for potential extremely dangerous truck drivers, especially in comparison with other types of truck drivers. Although many factors may affect driving behavior, because of data constraints, truck drivers' personal attributes (e.g., age, gender, education) and psychological conditions (e.g., upset, tired, angry) were ignored, and GPS data in this research was only used for extracting OD information. Furthermore, although the intuitive aspects of multilevel modeling are appealing, many challenges remain to its practical application and interpretation. Despite these limitations, this paper provides a systematic approach to identifying potential risks among different truck drivers that considers both macro and micro perspectives. We suggest that future work focus on the following four aspects. First, big data should be integrated with questionnaire survey data about truck drivers' personal characteristics and psychological factors. Second, more spatial information could be derived from GPS data. Third, effective data fusion approaches should be developed to support the above data integration and maximize statistical and epidemiological methods, deep learning techniques, and behavioral models. Finally, the above efforts should be extrapolated to implement practical safety improvements by developing effective decision support systems.

doi:<https://doi.org/10.1016/j.aap.2019.105256>. <https://www.sciencedirect.com/science/article/pii/S0001457519304737>.

**Brad's Notes:** Not the data we have.

Zhu, Mengtao, Yunjie Li, and Yinhai Wang. "Design and experiment verification of a novel analysis framework for recognition of driver injury patterns: From a multi-class classification perspective." *Accident Analysis & Prevention* 120 (2018): 152–164. doi:<https://doi.org/10.1016/j.aap.2018.08.011>. <https://www.sciencedirect.com/science/article/pii/S0001457518304524>.

**Brad's Notes:** Too Old

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Zhuang, Xiangling, and Changxu Wu. "Pedestrian gestures increase driver yielding at uncontrolled mid-block road crossings." *Accident Analysis & Prevention* 70 (2014): 235–244. doi:<https://doi.org/10.1016/j.aap.2013.12.015>. <https://www.sciencedirect.com/science/article/pii/S0001457513005125>.

**Brad's Notes:** Too Old

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Ziakopoulos, Apostolos, and George Yannis. "A review of spatial approaches in road safety." *Accident Analysis & Prevention* 135 (2020): 105323. doi:<https://doi.org/10.1016/j.aap.2019.105323>. <https://www.sciencedirect.com/science/article/pii/S0001457519309893>.

**Brad's Notes:** Interesting. Essential. This article will give me an overview of the vocabulary, techniques, and issues.

Zou, Xin, Hai L. Vu, and Helai Huang. "Fifty Years of Accident Analysis & Prevention: A Bibliometric and Scientometric Overview." *Accident Analysis & Prevention* 144 (2020): 105568. doi:<https://doi.org/10.1016/j.aap.2020.105568>. <https://www.sciencedirect.com/science/article/pii/S0001457519308772>.

**Brad's Notes:** Journal Metadata Analysis. Curious.

Zou, Xin, Wen Long Yue, and Hai Le Vu. "Visualization and analysis of mapping knowledge domain of road safety studies." *Accident Analysis & Prevention* 118 (2018): 131–145. doi:<https://doi.org/10.1016/j.aap.2018.06.010>. <https://www.sciencedirect.com/science/article/pii/S0001457518302744>.

**Brad's Notes:** Too Old

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