SEPERATING FACT FROM FICTION

THE BEST PRACTICE GUIDE TO UNDERSTANDING NEAR MISS CONFLICT ANALYTICS AND WHY THE RIGHT MACHINE-LEARNING MODELS AND METHODOLOGIES MATTER.

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Transportation Professionals Are Turning To Research-Based Near Miss Conflict Analytics To Predict And Mitigate Crash Risks

Road fatalities and severe accidents continue to inflict a high cost on communities. With more vehicles sharing roadways with bicycles, pedestrians, e-scooters, and other alternative modes of transportation, an aging population, and the advent of connected and autonomous vehicles, the risk of vehicle-to-vehicle and vehicle-to-vulnerable road user crashes continues to be a challenge for transportation planning, engineering, and operations professionals.

Many agencies still depend exclusively on historic crash and injury data to identify safety risks at intersections and other higher-risk sites on their roadways. However, there is a growing body of research and real-world implementations of new technologies to suggest that crash data alone is insufficient to make safety decisions and safety countermeasure investments because of lagging crash data, errors and incomplete data in crash reports, and small samples of reported vulnerable road user accidents.

This whitepaper, authored by industry-recognized leaders in road safety engineering, is designed to provide transportation professionals with a better understanding and recommended set of best practices for evaluating and selecting near-miss conflict analytics, including identifying those measurements, methodologies, and capabilities that are critical to accurately predicting and mitigating severe crashes through actionable insights and countermeasures.

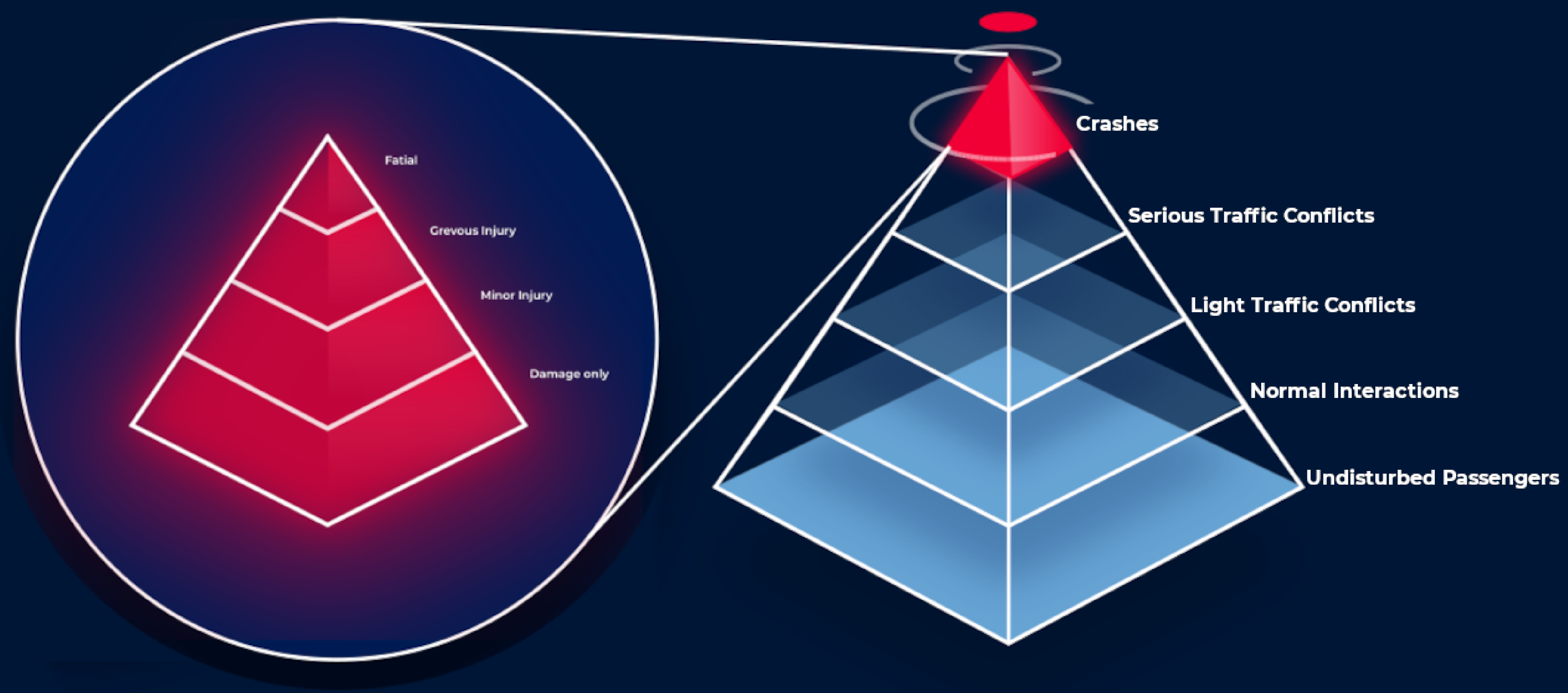
Does Your 'Near-Miss' Data Really Prove that there is a High Probability of Crash Risk?

What are 'Near-Misses' and Why Do They Matter?

Well-known limitations with the quality and timeliness of crash data and crash-based safety analysis methods are giving rise to the use of alternate measures of safety referred to as conflicts, or 'near-misses'. Conflicts describe events involving road users that demonstrate a high correlation with vehicle-vehicle and vehicle-vulnerable road user crashes.

Conflict data and analytics are critical to transportation planning, operations, and engineering because they offer a number of important advantages over historical crash data for road safety programs:

1. Conflicts occur much more frequently than crashes, and therefore, generate more robust datasets and insights that are critical for reliability.
2. Conflict data avoids the ethical dilemma of the need to first observe crashes in order to prevent them.
3. Conflict data provides instantaneous insights that can be used for real-time safety evaluation, countermeasure implementation, and traffic operation optimization, as opposed to lagging crash data.
4. Crash data does not provide insights into road user behavior, but conflict data can pool multiple data points to identify correlating factors for crash prediction.
5. Accident reports often include incorrect data, such as misidentifying hazardous road segments and blindspots while conflict data is using the same ground truth data.



Five Conflict Indicators that Matter

Presently, ‘near-miss’ events are being measured using a wide range of definitions. For example, depending on the provider, ‘near-miss’ is a term applied to measurements of a hard deceleration or acceleration, sudden lateral movement, or, simply the presence of a pedestrian and vehicle in the crosswalk area at the same time.

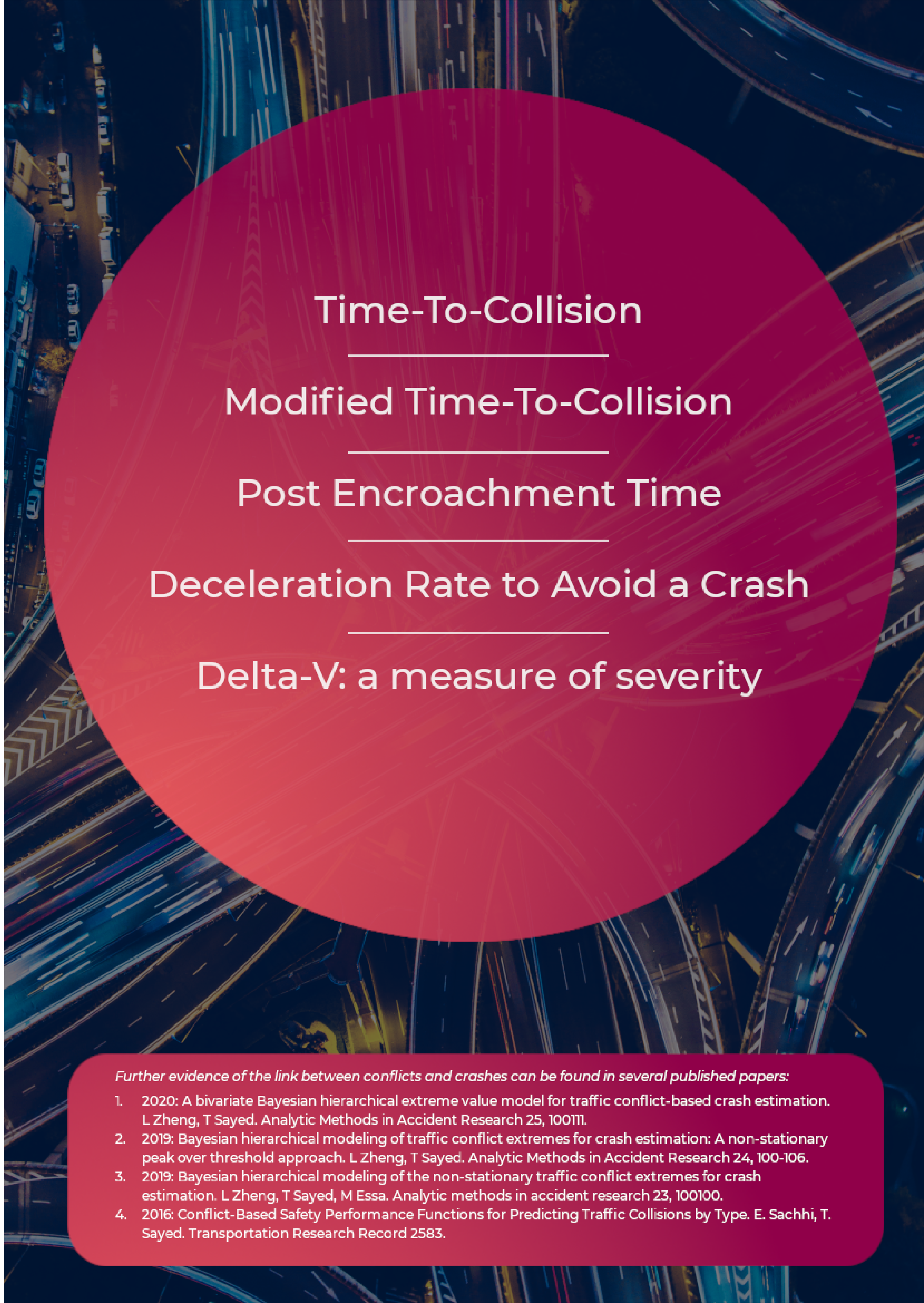
However, the only useful definition of a conflict is one that has a statistically proven relationship with observed crashes. Without such a proven relationship, these definitions of ‘near-miss’ may be merely correlated with levels of traffic, and are of no use in assessing road safety.

It is also important to recognize that conflicts include both remarkable and unremarkable events. A distinguishing feature of remarkable conflicts is evasive actions. While not an essential characteristic of a conflict, the presence of an evasive action--such as a pedestrian abruptly stopping or changing direction to avoid a crash, or a vehicle braking heavily or swerving to avoid a crash--is much more remarkable and reminiscent of crashes than are conflicts that do not involve evasive actions. Importantly, the relationship between conflicts and crashes does not depend on the presence of evasive actions.

Research has shown that understanding crash risk through conflict data requires the measurement of at least 5 unique indicators that have a proven ability to predict future crashes and crash severity. These include:

1. Time-To-Collision
2. Modified Time-To-Collision
3. Post Encroachment Time
4. Deceleration Rate to Avoid a Crash
5. Delta-V, a measure of severity

These measures have a proven ability to predict future crashes. As an example of this evidence, an evaluation of implementing Leading Pedestrian Intervals at signalized intersections in Bellevue, WA showed consistent results in the observed reduction in conflicts between pedestrians and vehicles as do reductions in vehicle-pedestrian crashes from crash-based studies.



Time-To-Collision

Modified Time-To-Collision

Post Encroachment Time

Deceleration Rate to Avoid a Crash

Delta-V: a measure of severity

Further evidence of the link between conflicts and crashes can be found in several published papers:

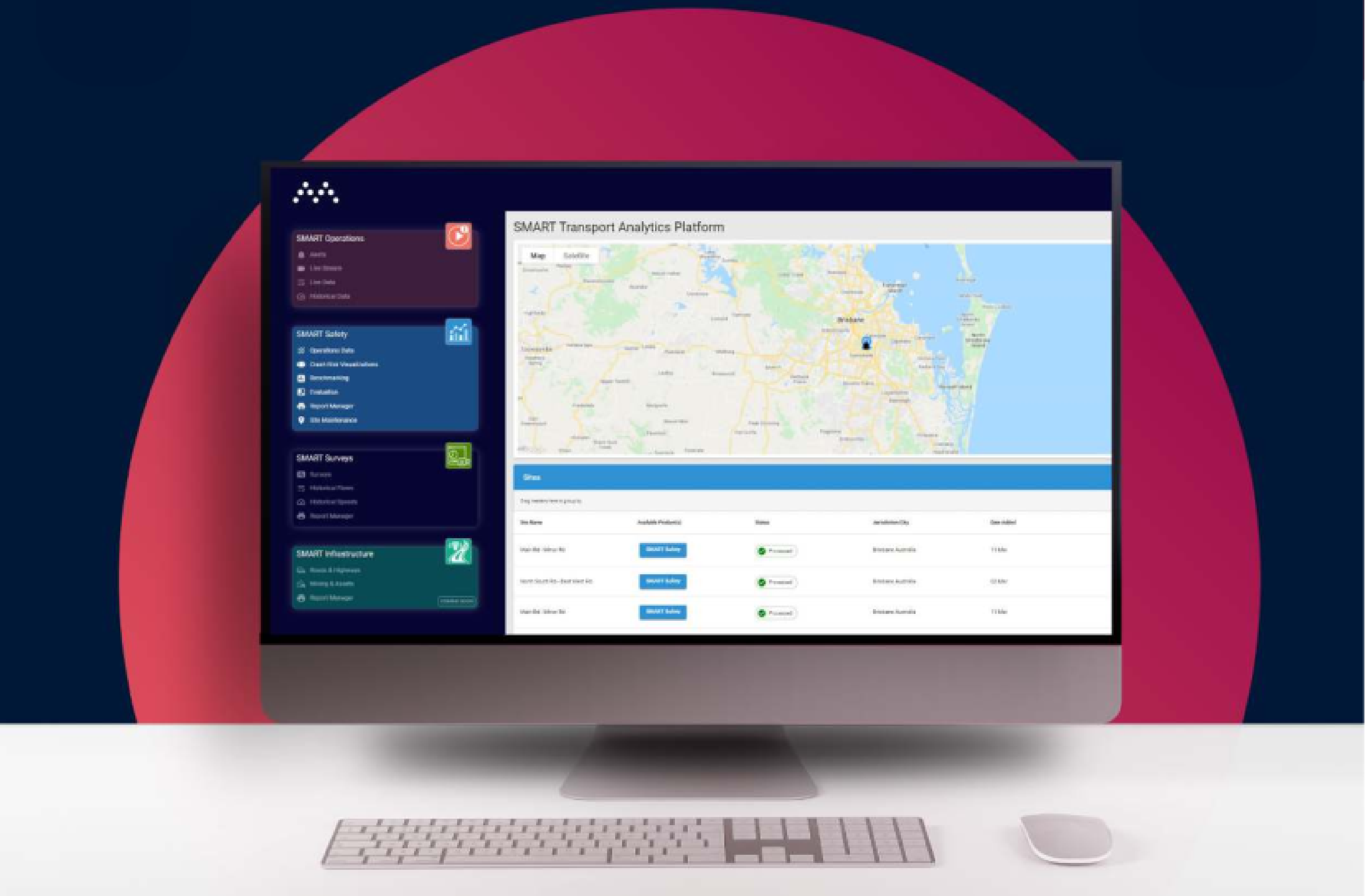
1. 2020: A bivariate Bayesian hierarchical extreme value model for traffic conflict-based crash estimation. L Zheng, T Sayed. Analytic Methods in Accident Research 25, 100111.
2. 2019: Bayesian hierarchical modeling of traffic conflict extremes for crash estimation: A non-stationary peak over threshold approach. L Zheng, T Sayed. Analytic Methods in Accident Research 24, 100-106.
3. 2019: Bayesian hierarchical modeling of the non-stationary traffic conflict extremes for crash estimation. L Zheng, T Sayed, M Essa. Analytic methods in accident research 23, 100100.
4. 2016: Conflict-Based Safety Performance Functions for Predicting Traffic Collisions by Type. E. Sachhi, T. Sayed. Transportation Research Record 2583.

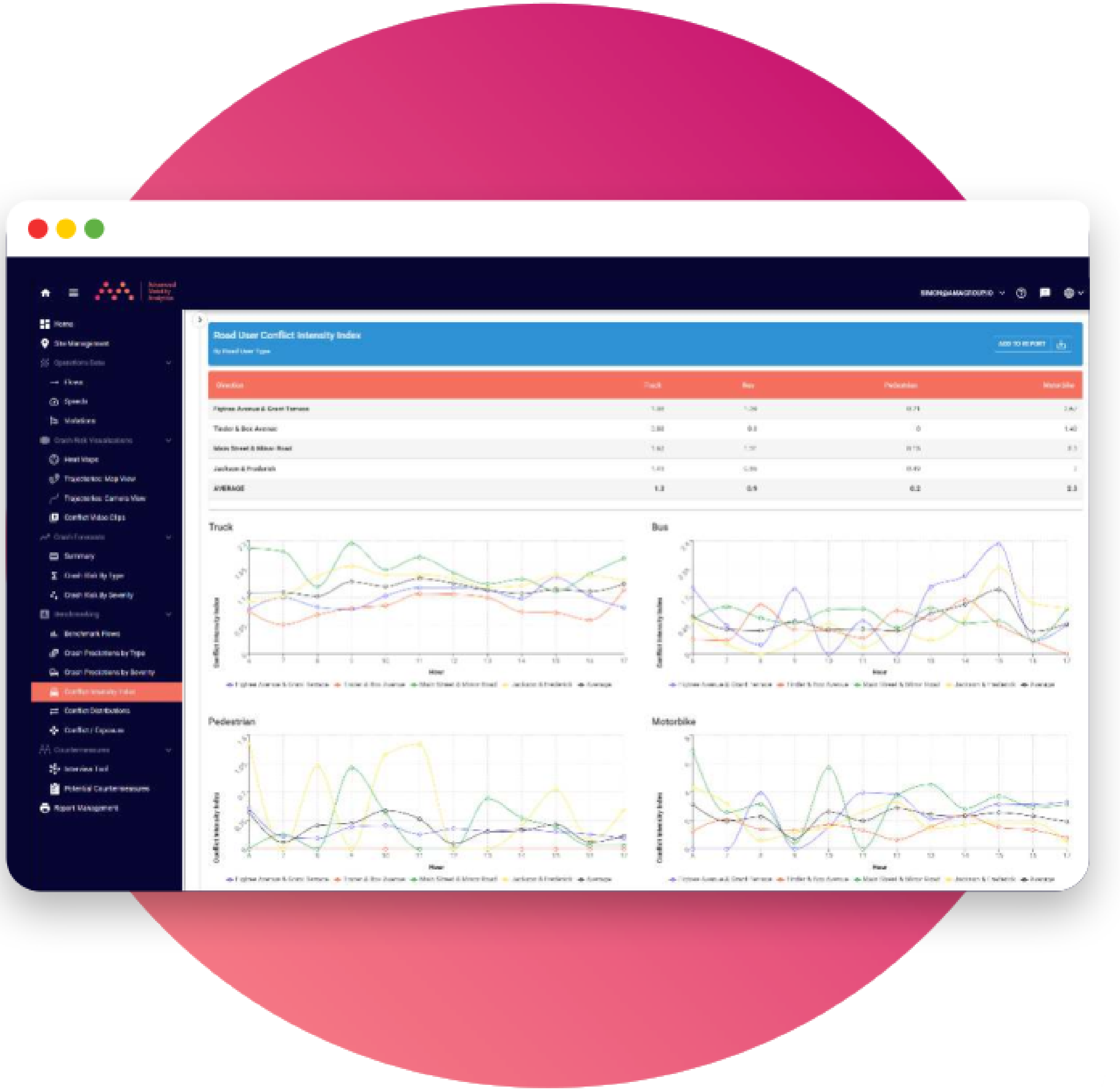
Ensuring Accuracy of 'Near-Miss' Data

The foundation of using conflicts to predict crash risk is built on the accuracy of the process to extract conflicts from sensor data. Research has shown that only extreme conflicts are the best predictors of crash risk and the identification of true extremes is highly sensitive to the quality of the conflict extraction process.

The accuracy of conflict extraction and their use to assess crash risk is very sensitive to several factors usually not considered. Ignoring these factors can completely bias the analysis. These include:

1. Road users are assumed to be represented by points (e.g., centroid, center of front bumper) and the road user size (e.g. vehicle size) is ignored. This can lead to significant errors in conflict indicator values.
2. When using video data, to accurately recover the positions of various road users, geometric elements need to be mapped back from camera image space to the world space. This mapping process is called "camera calibration" and is ignored in many systems that rely instead on tracking in the image pixels. Road user tracking in real-world coordinates significantly improves the accuracy of the tracking performance by correcting for perspective effects and other distortions due to projection on the image plane. Ignoring this step leads to significant errors in measuring quantities such as distances, speeds, deceleration and conflict indicators. Even if camera calibration is undertaken, a poor camera calibration can cause errors up to 1 sec in conflict indicators, a critical rate of error.
3. It is important to note that the relationship between conflicts and crashes varies by crash type and across jurisdictions. It is vital that a proven relationship exists between the crash type of interest and the conflict measure being used. Many systems available use only one conflict measure for all types of crashes.





Even with good, objectively defined conflict measures, it must be recognized that sensors do not provide perfect data. In conflict detection false positives and false negatives are inevitable, but they can be minimized in order to accurately predict crash risk. Extensive testing and validation is needed to refine the conflict extraction process to reduce false positives and negatives in order to include only those conflicts that are highly predictive of future crashes.

In addition to precise definitions of the 5 conflict measures required, numerous in-depth conditions should be applied to ensure accuracy. These conditions include:

1. Eliminating road user trajectories that are too short in length to provide reliable data.
2. Consideration of the speeds and angles between road users and eliminating data points that don't fall within acceptable and reasonable ranges. These ranges vary by specific encounter types (e.g. rear-end, sideswipe, right-angle).
3. Only calculating conflict measures at a frame of video if both road users are moving above a minimum speed, which can differ by site type.
4. After conflict measures are calculated, filtering these data based on threshold values, which can vary by conflict measure.
5. Keeping only conflicts that meet the threshold criteria for a minimum number of video frames, based on the number of frames per second recorded.

In Summary

Not all systems for extracting conflicts, or ‘near-misses’, are the same and the reliability of the results needs to be established before relying on them to evaluate safety.

Using conflict measures that haven’t been extensively validated against crash data is not useful for determining crash risk. It is important to recognize that not only are several conflict indicators required, but different crash types are related to different conflict types and with different threshold values. Furthermore, these relationships may change between jurisdictions with different traffic environments. The conflict extraction process must also take into account vehicle size and calibration of the camera, if using video data collection. Lastly, the application of additional criteria are required to minimize the number of false positives and false negatives. Not doing so may result in seemingly small errors that render the results meaningless.

About the Author

Craig Lyon has 25 years of experience as a road safety engineer focused on applied research projects. In 2020, Craig joined AMAG as General Manager for North America and Senior Road Safety Engineer. Craig has made significant contributions to the state-of-the-art knowledge in road safety found in the AASHTO Highway Safety Manual, including the development of statistical models for predicting crashes, road safety management analysis methods, and the development of crash modification factors (CMFs). Craig is recognized as an expert in the statistical analysis of safety data and was a long-time member of the Transportation Research Board Committee on Safety Performance Analysis.

Advanced Mobility Analytics Group Pty Ltd (AMAG) aims to be the world leading provider for proactive Transport analytics and management, applying more than 70+ years of cumulative road safety knowledge to develop the only complete Transport management suite of modules from Safety, Operations through to Infra-structure. Using Video Analytics, Artificial Intelligence (AI), Deep Learning, and Advanced Econometrics, AMAG has solved the challenge of predictive analytics for road safety, and during the past decade the founders have proven the methodology and technology through research, refinement, testing, and validation with 23 cities across 8 countries.

AMAG is focused on what we do best, road operational and safety insights through the best analytics solu-tions, developed by the best people. To deliver the best end-to-end SaaS Solution to road safety practitioners, we are partnering with the absolute best technology providers and engineering consultancy service providers across the globe.

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Contact Information

The headquarters for Advanced Mobility Analytics Group Pty Ltd is currently Brisbane Australia. AMAG is forging partnerships with companies in North America, Australasia, and Europe. The founders have worked in 8 countries globally and are forming additional partnerships currently. Interested SMART Platform users, investors, partners, collaborators, or clients can contact AMAG through the following channels:

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