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Incorporating Speed in a Traffic Conflict Severity Index to Estimate Left Turn Opposed Crashes at Signalized Intersections

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2 ABSTRACT 3

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4 Rigorous evaluation of implemented safety treatments, especially for innovative treatments and those 5 targeted at rare crash types, is challenging to accomplish with conventional crash-based analyses. This 6 paper aims to address this challenge for treatments at urban signalized intersections by providing a 7 methodology that uses surrogate measures of safety obtained from video analytics to predict changes in 8 crashes. To develop this approach, left turn opposed traffic conflicts based on post encroachment times, 9 along with corresponding conflicting vehicle speeds, are first measured from video observations at 10 signalized intersections. The conflicts are then classified into three severity levels using a risk score function 11 defined by these measures. Multiple linear regression models are developed to relate left turn opposed 12 crashes at the same intersections in the period 2009-2014 to the correspondingly classified conflicts. The 13 results show strong relationships between the classified conflicts and crashes (adjusted R^2 of 85% and 94%) 14 for total and fatal/injury crashes, respectively). The results also reveal that the contribution of conflicts to 15 the risk of crashes varies based on speed dimension of their severity, suggesting that neglecting speed as a 16 factor in conflict severity levels may be at the expense of losing meaningful information. The models can 17 be applied to estimate the change in crashes following a safety treatment by observing, through video 18 analytics, the change in conflicts and speeds and using the crash-conflict-speed model. The methodological 19 approach is viable for quickly evaluating all treatments and, in particular, innovative ones for which 20 knowledge on safety effects is sparse or non-existing.

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INTRODUCTION / BACKGROUND

25 The statistical analysis of crash data has traditionally been pursued to understand the safety of roads and to 26 develop suitable strategies to save lives and reduce injuries. Thanks to the progress in statistical 27 methodologies, researchers have been able to extract more accurate and useful information from crash data 28 sources. However, there are still several issues in safety analysis that mainly stem from the nature of crash 29 data sources. It is well-documented that police-reported data may be inaccurate and cannot provide as many 30 details as researchers would like (1). For example, crashes with no injury are less likely to be reported in 31 official crash databases (2), which in turn leads to erroneous inferences about the influence of variables (3). 32 This difficulty is compounded by the reality that crashes are rare events, and this may limit the ability to 33 draw solid conclusions about crash patterns and safety interventions. Elvik (4) mentions that "If a sample 34 is very small and/or has a very low mean number of accidents, it is just not possible to fit an accident model 35 to it". In addition to the rarity, crashes are complex events. More precisely, since they are caused by an 36 accumulation of multiple factors and failures (5), some factors may remain unobserved (e.g. information 37 about driver behavior and maneuver before the crash). Last, but not least, it can be argued that there is an 38 ethical point regarding crash data analysis in that using crash data is a reactive approach, and therefore, 39 there is a need to wait until a sufficient number of crashes takes place before dangerous sites can be 40 identified and corrected (6).

Due to the limitations in the use of crash data for safety inferences, using non-crash traffic events can be highly beneficial in many situations. The term safety surrogate measures (SSM) is used to refer to any events that can be correlated with crashes. Many factors through different techniques have been proposed to be used as SSMs, such as traffic volume, speed, delay, headway, and deceleration to safety time (7).

Traffic conflicts are the most widely used SSMs considered in highway safety analysis (7, 8). It can be argued that the typically one-year crash period is much longer than the period over which conflicts can be realistically observed and therefore that the process of generating conflicts may be different from the conditions resulting in crashes (7). However, it is well established that a conflict-based crash model can

50 be used to understand crash frequency (9, 10, 11, 12, 13, 14).

1 Traffic conflicts also can be further classified based on their severity and, based on their sheer 2 numbers compared to those for crashes, can be more informative for identifying safety concerns and 3 developing and evaluating remedies. Much of the previous SSM research has typically specified the severity 4 of a conflict by a variety of indicators of its proximity to a potential crash in terms of time or space. These 5 indicators may fall into four categories of Time-to-Collision (TTC) family, Post-Encroachment Time (PET) 6 family, Deceleration family, and other (the few indicators that do not fall within those families) (15).

7 The most prevalent indicators of traffic conflicts are the TTC and PET families. TTC is originally 8 defined by Hayward (16) as "...the time that remains until a collision between two vehicles would have 9 occurred if the collision course and speed difference are maintained". Also, a number of other indicators in 10 the TTC family exist that have been derived based on TTC, including Time Exposed TTC (17), Time-to-11 Zebra (18), Time-to-Line crossing (19), etc.

An alternative to the TTC concept is PET, which measures situations in which two road users are not on a collision course. As defined by Allen et al. (20), PET is the time between the moment that the first road user passes a certain point, and the moment that the second road user reaches that point. PET generally consists of two components: "(a) the conflict area and (b) the order in which two vehicles pass the conflict area" (21). At intersections, the TTC family measures work best when applied to rear-end conflicts, while PET has been suggested as the best measure for investigating angle conflicts, including those resulting from left turn opposed and cross-path movements (22). Figure 1 shows the calculation for TTC as defined by

19 Hayward (16) and for PET as defined by Allen et al. (20).

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Figure 1. $TTC=D/|\Delta V|$ (left) (adopted from Hayward (16)) and PET $(t_2 - t_1)$ (right) (adopted from Lord and Washington (21)).

STUDY OBJECTIVE AND OVERVIEW

The motivation for this paper's research was a need to build on the solid foundation of previous SSM research to better classify the severity of specific conflict types than by the mere frequency of close encounters that typically characterizes much of the previous research. The overall objective was to investigate a traffic conflict severity dimension to estimate crash prediction models for signalized intersections. To this end, the feasibility of obtaining meaningful relationships between conflicts from video observations and left turn opposed crashes was explored. These crashes can be quite severe, are often related to red-light running, and are the most prevalent among all left turn crashes. For example, in a sample of 197 four-legged signalized intersections collected in Florida left turn opposed crashes accounted for 72.5% of all left turn crashes (23).

Several systematic approaches have been proposed to combine various road safety cues to build macroscopic safety indices (24, 25), but a general consensus has not emerged on which approaches perform the best at the microscopic level for individual traffic events. This study is different from the main body of the literature in that it incorporates observed conflicting vehicle speeds to define a severity dimension of conflicts at signalized intersections.

1 To accomplish the research objective, vehicle-vehicle traffic conflicts based on PET, along with 2 corresponding conflicting vehicle speeds, were first measured from video observations at signalized 3 intersections in Winnipeg, Manitoba, Canada. Then, based on a novel approach, statistical models were 4 developed to relate these measures of conflicts frequency and severity to the recorded crashes at the same 5 intersections. The expectation is that such a methodological approach would be viable for quickly 6 evaluating all safety treatments and, in particular, innovative ones for which knowledge on safety effects is 7 sparse or non-existing. Specifically, it will facilitate inferences based on crash benefits that are essential for 8 cost-effectiveness analysis in prioritizing safety treatments. At the moment, such inferences are typically 9 based only on conflicts (26). The models and the overall video analytics process can also be used for 10 investigating and prioritizing specific locations that may be considered for application of these treatments. The rest of the paper is organized as follows. The next section summarizes the literature relevant to SSM 11 12 and the paper's objectives. The data description and the methodology behind the study are described in the 13 fourth section followed by sections that present and discuss the modeling results. Finally, the last section 14 summarizes the findings and makes suggestions for future research.

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17 REVIEW OF LITERATURE RELATED TO STUDY OBJECTIVES

As previously mentioned, several different measures have been proposed to represent the severity of a conflict. Although different measures have their own advantages, it is widely believed that TTC and PET are the best measures for the analysis of safety at intersections (22, 27). It is noteworthy while deceleration to avoid a crash (DRAC) has been receiving a growing interest, the current safety estimations using DRAC are still not reliable, which is likely related to the uncertainty of vehicle braking capacity (27).

24 Based on TTC or PET, a group of studies have defined a threshold to distinguish severe traffic 25 events from non-severe events. De Ceunynck (15) reviewed about 200 publications related to traffic 26 conflicts and observed that when a specific threshold value is applied for TTC, the threshold values of 1.5 27 sec., 2 sec., and 3 sec. are most common. Also, when applying PET, the use of a predefined threshold value 28 is less common compared to the studies applying TTC. As a relevant case to the objective of this research, 29 Peesapati et al. (13) evaluated the effectiveness of PET for examining the propensity of crashes between 30 left-turning vehicles and opposing through vehicles. A linear regression model was used to relate PET 31 measures and crashes. Their results showed that the selected threshold for PET (1 sec. in this case) plays 32 an important role in establishing its correlation with crashes. (The coefficient of determination, R^2 , in the 33 model based on a PET threshold of 2 sec. was 0.17, much lower than the value of 0.61 for a PET threshold 34 of 1 sec.) Using a negative binomial (NB) model, the same authors built upon their previous study to 35 investigate whether PET can be a substitute for intersection characteristics in crash prediction models (14). 36 They suggested that including AADT can potentially improve the estimations, but PET may be capturing 37 the effect of other intersection features such as sight distance and grade. They also found that the estimations 38 using linear regression may provide more robust results than the NB models.

39 A number of other studies aimed to "categorize" the severity of conflicts based on PET or TTC and 40 one or another factor. One of the earliest and most credible investigations has been conducted by Hydén 41 (28), and is the basis for the Swedish traffic conflict technique (TCT). In this study, traffic conflicts were 42 classified into uniform severity levels based on TTC and speed of the conflicting vehicles as seen in Figure 43 2, taken from an adaptation of the concept by Laureshyn et al. (29). To validate the proposed classification, 44 Hydén (28) used conflict-to-crash ratios for different "entities" and checked the "stability" and "similarity" 45 of the ratios by comparing the estimates and their confidence interval. As a general rule, he also suggested 46 a TTC threshold of 1.5 sec. to distinguish serious conflicts from slight conflicts. More recently, Laureshyn 47 et al. (29) defined the severity of conflicts based on Delta-V,



Figure 2. Conflict severity concept as adapted by Laureshyn et al. (29) from Hydén (28)

1234567 measured by calculating the expected change in speed between the pre- and post-crash, and a family of TTC that was designated as T₂; if the road users are on a collision course, T₂ is equal to the TTC, and if they are not on a collision course T₂ is the time for the latest-to-arrive road user. Their results suggest that indicators such as Delta-V can also potentially perform well at selecting the most severe traffic events.

8 Another early proposal to consider the severity of conflicts was based on TTC and a subjective 9 measure called the risk of collision (ROC) (30). In this, three levels for TTCmin (less than 2 sec., 1.6 sec., 10 and 1 sec.) and three levels of ROC (low, moderate, and high) are defined and, by adding them together, 11 the final severity is estimated. Sayed and Zein (31) used the data for 94 intersections in British Columbia 12 to validate the severity measure as defined by Brown (30). While the results confirmed a clear linear 13 relationship between conflicts and crashes for signalized intersections ($R^2 = 0.77$), the models for 14 unsignalized intersections displayed a very weak relationship ($R^2 = 0.20$).

15 From the data collection perspective, previous research has used trained human observers (28, 31), 16 microsimulation models (32, 33), and video analytics software (34, 35). Some studies (28) have shown that 17 using human judgment to collect conflict data can provide useful estimates. However, it is a well-18 established fact that humans are not good at estimating "purely time-based measures" (29). On the other 19 hand, while using microsimulation models can address this issue, they do not accurately take into account 20 the diversity and unpredictability of driver behavior existing in the real world.

21 Thanks to the advancement in sensor techniques and computer vision in recent years, more reliable 22 data can be assembled to build on previous research to open avenues to address new issues in safety 23 analysis, which would not have otherwise been possible. There is a growing interest in working on conflict 24 data automatically extracted using video recordings (11, 34, 36, 37), especially since it is relatively 25 inexpensive to deploy video cameras for traffic monitoring purposes; in fact, many jurisdictions (such as 26 Winnipeg that provided the data for this study) routinely deploy them for traffic observations and even for 27 security.

28 Among the more pertinent applications of video analytics for safety assessments was a study by 29 Essa and Sayed (37) who used data obtained by video recordings at six signalized intersections in two cities 30 of Canada to develop safety performance functions (SPFs) at the signal cycle level. Using generalized linear 31 models (GLM), with a negative binomial error structure, rear-end conflicts occurring in each cycle were 32 related to the variables such as traffic volume, shock wave characteristics, platoon ratio, and maximum 33 queue length. However, the developed models only relied on a single TTC threshold (1.5 sec.) to distinguish 34 between conflict and non-conflict events, without regard to severity of conflicts as manifested in vehicle 35 speeds. In a more recent study, Essa and Sayed (34) used a full Bayesian approach and the same data from 36 their previous paper to develop new conflict-based SPFs based on two other conflict indicators -- modified 37 TTC and deceleration rate. While the study uses different thresholds to take into account conflict severity 38 levels, the developed models are still principally based on one or the other conflict indicator (e.g., one 39 model estimates number of conflicts having a deceleration rate more than 4 m/sec^2 , and another model 40 estimates number of conflicts having a TTC less than 2 sec., etc.).

1 In sum, it seems reasonable to conclude that the literature regarding the relation between crashes 2 and conflicts with different severity levels is incomplete, although there has been significant promise in 3 some of the approaches investigated. This study sought to build on that promise by mapping composite 4 measures of conflicts into the severity dimension in order to establish relationships between the seriousness 5 6 and frequency of conflicts and the risk of crashes.

8 **METHODOLOGY**

9 Data

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11 The data used in this study were obtained from MicroTraffic, a company that provided the conflict data 12 from video files provided by the City of Winnipeg, who also supplied the traffic and crash data. The video 13 recordings pertained to 15 urban signalized intersections, comprised of 12 with 4 legs and 3 with 3 legs. 14 All were semi-actuated and had left turn auxiliary/storage lanes on all approaches. For 13 intersections, the 15 video was 24 hours long while the other 2 intersections had 7.5 and 9 hours for video. Peak and off-peak 16 hours were observed at all intersections. High-definition cameras were used to collect the data from an 17 elevated viewpoint, so that they can potentially capture the movements made at all the intersection 18 approaches. The viewpoints of two approaches in two different intersections were blocked, and thus, both 19 the conflicts and crashes related to these approaches were excluded from the dataset. Figure 3 shows an 20 intersection with the custom software interface- i.e., the green lines represent the paths of the vehicles. 21



Figure 3. A sample intersection in the software

The recordings were analyzed based on road user trajectories that were automatically extracted 26 using video analytics software to derive two measures of vehicle-vehicle conflicts -- PET and conflicting vehicles speeds. The first part of the computer vision system is the detector, which uses a deep learning 27 28 neural network to identify road users in every frame of the video and assign them to a class such as vehicle, 29 pedestrian, cyclist, or e-scooter. The second part is a tracker which uses algorithms to link individual road 30 users from frame to frame into tracks. The third part of the computer vision system converts the tracks in 31 pixel space to real world coordinates, using a spatial homography, scaling, and dynamic parallax correction. 32 The result is a real-world trajectory file. Conflicts are determined by an algorithm that compares trajectories 33 to one another based on rules set by the analyst, such as PET, speed, user type, and movement types of 34 involved users. Figure 4 shows a sample road user trajectory development with the colors representing 35 different turning movements. Near misses are detected by automatically searching through these trajectories 36 to determine cases when collisions were narrowly avoided. For every vehicle-vehicle conflict, the data 37 extracted included the movement direction and the speed (with 2 km/hr accuracy) of each conflicting 38 vehicle for PET less than 5 sec. (with 0.1 sec. accuracy). In other words, any traffic event between two 39 vehicles, one through direction vehicle and one the opposite left-turning vehicle where the turning vehicle 40 passed in front of the through vehicle, with a PET threshold of 5 sec. or less is referred to as a traffic conflict. 41

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Figure 4. The interface of the software for a sample road user trajectory development

23 4 5 6 Traffic data included the traffic volume for each approach and the traffic volumes for through, left turn, right turn and U-turn movements. The count durations ranged from 4 to 10 hours.

7 Crash records for the 6-year period from 2009-2014, the latest years available for the study, were 8 assembled. This rich dataset included information such as injury severity (property damage only (PDO), 9 non-fatal injury, or fatal), collision impact type, pavement condition, and vehicle movement directions. The 10 left turn opposed crashes were separately extracted for each approach and then they were added together to 11 produce the total number of such crashes at that intersection.

12 Table 1 presents the descriptive statistics of the data. Not surprisingly, the mean value of 3.94 sec. 13 for PET implies that the majority of the recorded conflicts are not relatively severe. The mean value of 14 74.41 km/hr for the summation of through and left turn speeds also seems to be consistent with the 15 expectations. Regarding traffic volume, Table 1 also shows through movement has noticeably larger traffic 16 volume compared to the left turn movement. In addition, in terms of crashes, there is a significant variation 17 in the frequency of left turn opposed crashes, ranging from as many as 20 to as few as zero.

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Variable	Mean	St.Dev	Min	Max
PET (sec)	3.94	0.93	0.07	5.00
Summation of conflicting speeds (km/hr)	74.41	21.18	8.02	186.87
Speed limit (km/hr)	71.89	11.07	50	90
Through traffic volume (veh/hr)	713.97	876.37	678.62	3665.75
Left turn traffic volume (veh/hr)	169.18	204.75	192.37	893.5
Total crashes for 6 years	4.62	5.72	0	20
Injury crashes for 6 years	1.73	2.08	0	6

Table 1. Descriptive statistics of the data

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21 22 Modeling procedure overview

23 The focus of this SSM analysis was on the conflicts between the through (Thru) and left turn (LT) 24 movements on opposing approaches. Given the PET and speed of the conflicting vehicles, the objective 25 was to establish a relationship between the frequency and severity of these conflicts and the associated

1 collisions at urban signalized intersections. To this end, only Thru-LT conflicts were extracted from the 2 video data and only opposing Thru-LT collisions were used.

3 The main step in the procedure was the classification of conflicts into uniform severity levels. The 4 classification process includes: a) establishing a PET threshold identifying conflicts that will be used for 5 the further evaluation and b) defining a Risk Score (RS) function used to classify these conflicts by severity, 6 considering speeds of conflicting vehicles. The RS provides a continuous function that maps the conflicts 7 measures into a severity dimension. To build uniform severity levels similar to the concept shown in Figure 8 2, a relationship was then established between conflicts categorized according to RS and the recorded 9 collisions. The estimation of this relationship was carried out using multiple linear regression model, in 10 which the dependent variable is the number of collisions per year and the independent variables are the number of conflicts in different levels categorized by RS. To investigate the crash-conflict relationship 11 12 based on different PET thresholds, following other studies (13, 14), different thresholds of PET were tested 13 iteratively. It was found that a PET threshold of 2 sec. provides the most accurate results. Figure 5 plots the 14 total left turn opposed crashes per year versus the number of conflicts with PET less than 2 sec. per hour. 15 Visually a strong correlation is indicated and a linear function seems appropriate for the crash-conflict 16 relationship. (There were 5 intersections represented as single point on the plot that had neither crashes nor 17 conflicts with PET less than 2 sec.) As discussed in the literature review, previous studies have also found

18 that the crash-conflict relationship may be well represented in a linear form (9, 13, 14).





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Figure 5. Number of conflicts with a PET less than 2 sec. versus total crashes

23 The selection of the RS thresholds was based on an iterative process similar to that used by 24 Peesapati (14). The objective was to ascertain the thresholds that provide the best-fit model in terms of the 25 coefficient of determination, statistical significance of the parameters, and the intuitiveness of the estimated 26 parameters. At the same time, different PET threshold values ranging from 1 sec. to 5 sec. were separately 27 evaluated to identify RS thresholds that provide a reasonable amount of conflicts in each category. For 28 illustration, thresholds T_1 and T_2 may be determined in this process such that the conflicts would be 29 categorized according to RS < T_1 (lowest severity category), those having $T_1 \leq$ RS < T_2 , and those that have 30 $RS \ge T_2$ (highest severity category). Separate models were developed for total crashes and fatal plus injury 31 32 (FI) crashes.

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35 **ANALYSIS AND RESULTS**

Different PET threshold values ranged from 1 sec. to 5 sec., with the interval of 0.5 sec., were employed to determine which PET thresholds give the best-fit model for total and FI crashes separately. The criteria to select the thresholds in this iterative process, as noted earlier, include the relative accuracy of the model in terms of the coefficient of determination, statistical significance of the parameters, and the intuitiveness of the estimated parameters.
Regarding total crashes, it was found that a PET threshold of 5 sec. provides the best accuracy,

Regarding total crashes, it was found that a PET threshold of 5 sec. provides the best accuracy,
suggesting that the conflicts up to this value can be potentially meaningful for establishing a crash-conflict
relationship. For FI crashes, the results suggest that focusing on those conflicts having a PET less than 2.5
sec. gives the most accurate predictions. In other words, given a crash has happened, it is intuitive to expect
the probability of having an injury in the crash will be low when PET is more than 2.5 sec.

11 The link function, which helps to relate the conflict measures to the severity of conflicts, can be 12 generally categorized as linear (e.g., RS=PET) (38), or nonlinear (e.g., RS=1/PET) (39). A linear 13 assumption in conflict severity implies that, for example, a conflict with a PET of 1 sec. is twice as severe 14 as a conflict with a PET of 2 sec. and a conflict with PET of 2 sec. is again twice as severe as a conflict 15 with a PET of 4 sec. However, it can be argued that this linear assumption is somewhat unreasonable. This 16 is because the link function should be able to capture the nonlinearity in the severity of conflicts by 17 enlarging the severity differences among small values of conflict measures and narrowing the differences 18 among the higher values (40). The nonlinearity of the link function in the previous studies has been 19 represented either in a reciprocal form (39), or an exponential form (41, 42). The link function proposed 20 here is generally in a reciprocal form, in which the PET is transformed to an exponential form to potentially 21 enlarge the effects of PET in lower values. Exponential transformation of conflict measures can also be 22 found in the previous studies (41). In addition to PET, the risk score (RS) is intended to reflect the effect of 23 conflicting speeds. In this regard, the summation of Thru and LT vehicle speeds was used to take into 24 consideration the effect of speed in the conflict severity as follows:

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28 Based on the values of conflicting speed and PET in the dataset, the possible values of the RS range 29 from 0.07 to 76. Figure 6 displays how the RS changes based on the variation in the sum of conflicting 30 speeds and PET. To better visualize the variations, the plot includes those conflicts that have a PET larger 31 than or equal to 1 sec. It is noted that, of the 2,680 conflicts recorded, 13 of them had a PET less than 1 32 sec., for which a summation of speed of conflicting vehicles of 55 km/hr can result in RS>20. As seen, the 33 conflict severity may significantly differ according to the conflicting speed. For instance, a conflict having 34 a PET of 2 sec., can yield an RS of less than 10 when the sum of conflicting vehicle speeds is 60 km/hr, 35 while a sum of 140 km/hr may lead to an RS of about 19 for the same PET of 2 sec.

 $RS = \frac{Speed \ of \ Thru \ movement + Speed \ of \ LT \ movement}{}$

 e^{PET}

(1)



Figure 6. Visualization of the proposed RS for different values of conflicting speed and PET.

Having the function, the conflicts were categorized into more severe and less severe classes, with larger RS conflicts being more severe. Multiple linear regression models were then developed to establish a relationship between the three categories of conflicts with left turn opposed crashes. It should be noted traffic volume was also included in the model development process; however, since it did not improve the model it was removed from the final models. Specifically, the coefficient of the parameters related to left turn and through traffic volumes were not significant, which could be explained by the correlation that 9 exists between traffic volume and number of conflicts (10, 13). The results of linear regression models are shown in Tables 2 and 3 for total crashes and FI crashes.

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Table ₂ .	Results	of	total	crash	model
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	Coeff.	St. Error	t Stat	P-value	Lower 90.0%	Upper 90.0%
Intercept	0	-	-	-	-	-
RS < 16	0.029	0.016	1.860	0.088	0.001	0.057
$16 \le \text{RS} < 21$	3.046	1.705	1.786	0.099	0.007	6.085
RS ≥21	4.061	1.238	3.280	0.007	1.854	6.268
Regression Statistics: $R^2 = 0.94$						
	А	djusted $R^2 =$	0.85			
	S	tandard error	of regres	sion= 0.321		

Table3. Results of FI crash model

	Coeff.	St. Error	t Stat	P-value	Lower 95.0%	Upper 95.0%
Intercept	0.034	0.031	n/a ¹	n/a ¹	-0.034	0.102
RS < 12	0.131	0.077	1.697	0.118	-0.039	0.300
$12 \le \text{RS} < 17$	0.814	0.253	3.216	0.008	0.257	1.371
RS ≥17	0.896	0.204	4.381	0.001	0.446	1.346
Regression Statist	ics:	$R^2 = 0.96$				
		Adjusted R ²	$^{2} = 0.94$			
		Standard er	ror of reg	ression= 0.	087	
n/a = not applic	able					

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18 Regarding the total crashes model, the results in Table 2 indicate that, when focusing on those 19 conflicts with a PET less than or equal to 5 sec., the RS=21 and RS=16 thresholds can be used to classify 20 the conflicts into three categories by their severities. The selection of these thresholds, as noted earlier, was 21 based on an iterative process in which the accuracy of the models, the significance of the parameters, and 22 the intuitiveness of the estimates were considered. As seen in Table 2, the coefficients estimated for all 23 three categories are significant at the 10% level of significance, and intuitive in terms of the direction and 24 relative magnitude of the effects; for example, those conflicts having an RS more than 21 are much more critical than those with an RS less than 16. The estimated value of the adjusted $R^2 = 0.85$ implies that 85% 25 of the variability of Thru-LT collisions can be captured by the estimated model. (Adjusted R^2 is a modified 26 27 form of R^2 , which is based on the number of predictors in the model; the value only increases when the 28 new variable improves the model more than would be expected by chance.) Moreover, since it is reasonable 29 to expect that there is no exposure to the risk of collision for the traffic events having a PET larger than 5 30 sec., an intercept of zero was forced such that zero crashes are predicted if there is no conflict with PET<5 31 sec. The intercept, by definition, is the mean of the response when all predictors are zero.

32 Similarly, conflicts have been categorized into three categories for the FI crashes. As seen in Table 33 3, the coefficients for the two severe categories were significant at the 5% level, and for the less severe

1 category at the 15% level. The model suggests that those conflicts with RS \geq 17 have 1.1 and 6.8 times 2 greater contribution to crash occurrence compared to those with $12 \leq RS < 17$ and RS < 12, respectively. 3 The estimated value of the adjusted R^2 of 0.94 suggests that 94% of the variability of FI Thru-LT collisions 4 can be captured by the estimated model. Note that, in contrast to the total crashes model, an intercept has 5 been used for the FI crashes model. This is because there is a reasonable possibility of FI crashes occurring 6 when there are no conflicts with PET<2.5 sec.

With the results in Table 2 and 3, the number of total and FI crashes per year at an intersection can be calculated as follows:

 $N_{Total} = 0.029 \text{ (Conf. RS} < 16) + 3.046 \text{ (Conf. } 16 \le RS < 21) + 4.061 \text{ (Conf. RS} \ge 21)$ (2)

 $N_{FI} = 0.034 + 0.131 \text{ (Conf. RS} < 12) + 0.814 \text{ (Conf. } 12 \le RS < 17) + 0.896 \text{ (Conf. RS} \ge 17)$ (3)

where Conf. stands for the number of conflicts per hour in each category.

For a sample intersection in the city of Winnipeg, Figure 7 visually depicts how the conflicts observed during a 24-hour period are distributed in the three proposed categories for total and FI crash prediction models. As seen for the total crash model, for example, there are 355, 6, and 9 conflicts in the categories 1, 2, and 3, respectively. Figure 7 also illustrates how the proposed approach incorporating speed can be different from a single threshold approach. For instance, there are 15 conflicts observed with a PET within the range of 1.5 sec. and 2 sec. With a single threshold approach, expanding the threshold from 1.5 sec. to 2 sec. requires that all 15 conflicts be used and treated equally for the crash-conflict relationship. However, using the proposed approach, 7 conflicts lie in the least severity category, 2 in the medium severity category, and 6 in the most severe category. This consideration of severity will, in principle, provide more robust models than the single threshold approach.

It is worth noting that, since the total crash model includes all the conflicts with PET up to 5 sec., there is a remarkably larger number of conflicts in the least severe category (those above the blue line) compared to the same category in the FI crash model which only considers the conflicts with PET less than 2.5 sec.



Figure 7. Conflict categories for a sample intersection in the city of Winnipeg (Left=Total crashes and Right=FI crashes).

Figure 8 plots the observed and predicted total and FI crashes for the 15 studied Winnipeg intersections. As seen by the diagonal "equality" line, even though the observed crashes are short term counts that are naturally expected to vary from the mean, the predicted crashes closely track to the observed crashes and there is no overestimation or underestimation for any particular range of crashes.

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Figure 8. Relationship between observed and predicted for total (left) and FI (right) crashes.

4 It is informative to compare the results of this study to what is perhaps the most relevant study from the 5 6 literature -- one by Peesapati et al. (13), who focused on left turn opposed crashes, and used PET collected from video data as a surrogate measure to define the conflicts. Their results suggested that focusing on 7 those conflicts with PET less than 1 sec. provides the best crash-conflict relationship. However, as noted 8 earlier, the models were merely based on PET thresholds and that may explain why such a small value 9 provided the most accurate predictions. This comparison highlights that adopting a single PET threshold to 10 distinguish between conflicts and non-conflict events may be at the expense of losing potentially 11 meaningful information. For illustration, in the sample of 15 Winnipeg intersections used in the current 12 study, there are 91 conflicts that have a PET<2 sec. However, in the proposed classification, which takes the conflicting speed into account, 51 (57%) of these conflicts are considered to be critical. On the other 13 14 hand, only 13 conflicts in the dataset have a PET<1 sec., indicating that using a single PET threshold with 15 this value for modeling would have ignored 38 meaningful conflicts.

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20 CONCLUSIONS

The main objective of this study was to establish a relationship between surrogate measures of safety and crashes at signalized intersections. In this regard, vehicle-vehicle traffic conflicts based on post encroachment times, along with corresponding conflicting vehicle speeds, were first measured from video observations at signalized intersections in Winnipeg region, Manitoba. Using a risk score function, the conflicts were categorized into different severity levels. Then, multiple linear regression models were developed to relate left turn opposed crashes at the same intersections to the corresponding conflicts that are classified by severity.

29 The results of this research demonstrate the potential of using these measures to quantify the safety 30 of an intersection. In terms of model fit, coefficients, and significance level of the covariates, the models 31 revealed that the approach taken provides promising results for the data used. For the data used, the adjusted 32 R^2 in the total and fatal/injury crash models were found to be 85% and 94%, respectively. The model 33 coefficients also imply that those conflicts that are categorized as more severe have considerably larger 34 effects on crash occurrence compared to those categorized as less severe. For example, the coefficient for 35 the proposed most severe category is approximately 140 times as large as that for the least severe category 36 in the total crash model. This emphasizes the need for a proper classification of conflicts based on their 37 severities and suggests that using a single time-based threshold, such as PET or TTC, may not be adequate. 38 Analyzing video data of road facilities for detection of conflicts presents an unprecedented 39 opportunity to harness as much data as possible that will provide insight into possible conflict situations

1 and make it easier to suggest effective treatment strategies. As such, there can be numerous applications 2 using the conflict technique proposed. Importantly, the results of this study highlight the importance of 3 incorporating conflicting vehicle speeds to estimate the effects of safety treatments at signalized 4 intersections. Candidate treatments aiming at reduction of conflicting speed, such as warning flashers used 5 to alert drivers of potential traffic-signal changes, may be considered for such safety evaluation. Using 6 conflict data extracted by video-analytics software and applying the models developed, the effectiveness of 7 such treatments on left turn opposed crashes could be potentially understood in a very short period of time. 8 The premise of the approach is that a safety treatment may alter the frequency of conflicts and the speed of 9 conflicting vehicles but will not change the relationship between those variables and corresponding crashes. 10 Of especial interest is that this approach is viable for quickly evaluating the crash benefits of treatments, in 11 particular, innovative ones for which knowledge on safety effects is sparse or non-existing. The models developed and the overall video analytics process can also be used for investigating and prioritizing specific 12 13 locations that may be considered for application of these treatments.

14 In general, the limitation of data may restrict the results to the jurisdictions examined. The proposed models were based on 15 intersections in the city of Winnipeg, and crash data for an earlier period. While 15 16 the results of the models are promising, they may not be generalizable to other jurisdictions that may not 17 have the technology and skill sets to develop their own models. There may be major differences in terms 18 of traffic conditions and intersection geometry, which could significantly affect the transferability of the 19 results to other jurisdictions and future time periods. However, what is transferable is the methodological 20 approach. In terms of future research, an evaluation of the approach, and the transferability of the modeling 21 results, can be undertaken on data collected from other regions where the operational characteristics and 22 the geometry differ from the data used in this research. Moreover, currently the approach has only been 23 developed for treatments targeting left turn opposed crashes at signalized intersections and is based on a 24 relatively small sample. It should and could be expanded for a larger sample and for other crash and site 25 types, including pedestrian crashes. Future research should also be directed at designing before-after 26 conflict studies in terms of sample sizes for treatment and control sites, and at evaluation methodologies 27 that would account for traffic volume changes and regression-to-the-mean while providing estimates of the 28 uncertainty in the safety effects calculated from applying the models.

29 REFERENCES

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- 1. Mannering FL, Bhat CR. Analytic methods in accident research: Methodological frontier and future directions. Analytic methods in accident research. 2014 Jan 1:1:1-22.
- 2. Yamamoto T, Hashiji J, Shankar VN. Underreporting in traffic accident data, bias in parameters and the structure of injury severity models. Accident Analysis & Prevention. 2008 Jul 1;40(4):1320-9.
- 36 3. Lord D, Mannering F. The statistical analysis of crash-frequency data: a review and assessment of 37 methodological alternatives. Transportation research part A: policy and practice. 2010 Jun 38 1:44(5):291-305. 39
 - 4. Elvik R. Assessing causality in multivariate accident models. Accident Analysis & Prevention. 2011 Jan 1;43(1):253-64.
- 41 5. Reason J, Hollnagel E, Paries J. Revisiting the Swiss cheese model of accidents. Journal of 42 Clinical Engineering. 2006 Oct;27(4):110-5. 43
 - 6. Chin HC, Quek ST. Measurement of traffic conflicts. Safety Science. 1997 Aug 1;26(3):169-85.
- 44 7. Tarko A, Davis G, Saunier N, Sayed T, Washington S. Surrogate measures of safety-White paper. 45 Transportation Research Board, Washington, DC. 2009 Jan. 46
 - 8. Tarko A. Measuring Road Safety with Surrogate Events. Elsevier; 2019 Nov 7.
- 47 9. Sayed T, Zein S. Traffic conflict standards for intersections. Transportation Planning and 48 Technology. 1999 Aug 1:22(4):309-23.
- 49 10. Guo F, Klauer SG, Hankey JM, Dingus TA. Near crashes as crash surrogate for naturalistic 50 driving studies. Transportation Research Record. 2010 Jan;2147(1):66-74.

1	11.	El-Basyouny K, Sayed T. Safety performance functions using traffic conflicts. Safety science.
2		2013 Jan 1;51(1):160-4.
3	12.	Wu KF, Jovanis PP. Crashes and crash-surrogate events: Exploratory modeling with naturalistic
4		driving data. Accident Analysis & Prevention. 2012 Mar 1:45:507-16.
5	13.	Peesapati LN, Hunter MP, Rodgers MO, Evaluation of postencroachment time as surrogate for
6	-	opposing left-turn crashes. Transportation research record. 2013 Jan:2386(1):42-51.
7	14	Peesapati LN Hunter MP Rodgers MO Can nost encroachment time substitute intersection
8	1	characteristics in crash prediction models? Journal of safety research 2018 Sep 1:66:205-11
9	15	De Counvnek T. Defining and applying surrogate safety measures and behavioural indicators
10	15.	through site based observations. Hasselt University: 2017
10	16	House of a scale of danger Deport TTSC 7115
11	10.	University Dark. The Denneylyania State University 1072
12	17	Mindenhand MM. Derry DIL Entended time to collision measures for read to ffic enfots.
13	1/.	Winderhoud Wivi, Bovy PH. Extended time-to-collision measures for road traffic safety
14	10	assessment. Accident Analysis & Prevention. 2001 Jan 1;33(1):89-97.
15	18.	Varhelyi A. Drivers' speed behaviour at a zebra crossing: a case study. Accident Analysis &
16		Prevention. 1998 Nov 1;30(6):/31-43.
17	19.	van Winsum W, Brookhuis KA, de Waard D. A comparison of different ways to approximate
18		time-to-line crossing (TLC) during car driving. Accident Analysis & Prevention. 2000 Jan
19		1;32(1):47-56.
20	20.	Allen BL, Shin BT, Cooper PJ. Analysis of traffic conflicts and collisions. Transportation
21		Research Record. 1978. No. 667.
22	21.	Lord D, Washington S, editors. Safe mobility: Challenges, methodology and solutions. Emerald
23		Publishing; 2018 Apr 18.
24	22.	Alhajyaseen WK. The development of conflict index for the safety assessment of intersections
25		considering crash probability and severity. Procedia computer science. 2014 Jan 1;32:364-71.
26	23.	Wang X, Abdel-Aty M. Analysis of left-turn crash injury severity by conflicting pattern using
27		partial proportional odds models. Accident Analysis & Prevention. 2008 Sep 1;40(5):1674-82.
28	24.	Hu W, Xiao X, Xie D, Tan T, Maybank S. Traffic accident prediction using 3-D model-based
29		vehicle tracking, IEEE transactions on vehicular technology, 2004 May 24:53(3):677-94.
30	25.	Hermans E. Van den Bossche F. Wets G. Uncertainty assessment of the road safety index.
31	-	Reliability Engineering & System Safety, 2009 Jul 1:94(7):1220-8.
32	26	Strauss J. Zangenehpour S. Miranda-Moreno LF. Saunier N. Cyclist deceleration rate as surrogate
33	20.	safety measure in Montreal using smarthhone GPS data Accident Analysis & Prevention 2017
34		Feb 1.99.287-96
35	27	Zheng L. Saved T. Comparison of traffic conflict indicators for crash estimation using neak over
36	27.	threshold approach. Transportation research record, 2010 May: 2673(5):403-502
30	28	Hydén C. The development of a method for traffic safety evaluation: The Swedish Traffic
20	20.	Conflicts Technique, Dulletin Lund Institute of Technology, Department, 1087(70)
20 20	20	Leurenhaut, De Ceurenelt T. Kerlegen C. Sterregen & Deniels S. In general of the ceurenity
39 40	29.	Lauresnyn A, De Ceunynck T, Karisson C, Svensson A, Daniels S. In search of the sevenity
40		dimension of traffic events: Extended Delta- v as a traffic conflict indicator. Accident Analysis &
41	20	Prevention. 2017 Jan 1;98:46-56.
42	30.	Brown GR. Traffic conflicts for road user safety studies. Canadian Journal of Civil Engineering.
43		1994 Feb 1;21(1):1-5.
44	31.	Sayed T, Zein S. Traffic conflict standards for intersections. Transportation Planning and
45		Technology. 1999 Aug 1;22(4):309-23.
46	32.	Caliendo C, Guida M. Microsimulation approach for predicting crashes at unsignalized
47		intersections using traffic conflicts. Journal of transportation engineering. 2012 Dec
48		1;138(12):1453-67.
49	33.	Qin L, Persaud B, Saleem T. Safety evaluation of freeway acceleration lanes based on crashes
50		and simulated conflicts. Canadian Journal of Civil Engineering. 2018;45(1):51-60.

1 34. Essa M, Saved T, Full Bayesian conflict-based models for real time safety evaluation of 2 signalized intersections. Accident Analysis & Prevention. 2019 Aug 1;129:367-81. 3 35. Autey J, Sayed T, Zaki MH. Safety evaluation of right-turn smart channels using automated 4 traffic conflict analysis. Accident Analysis & Prevention. 2012 Mar 1:45:120-30. 5 36. Saunier N, Sayed T. Automated analysis of road safety with video data. Transportation Research 6 Record. 2007 Jan;2019(1):57-64. 7 37. Essa M, Sayed T. Traffic conflict models to evaluate the safety of signalized intersections at the 8 cycle level. Transportation research part C: emerging technologies. 2018 Apr 1;89:289-302. 9 38. Songchitruksa P, Tarko AP. The extreme value theory approach to safety estimation. Accident 10 Analysis & Prevention. 2006 Jul 1;38(4):811-22. 11 39. Zheng L, Ismail K, Meng X. Shifted Gamma-Generalized Pareto Distribution model to map the 12 safety continuum and estimate crashes. Safety Science. 2014 Apr 1;64:155-62. 13 40. Zheng L, Ismail K. A generalized exponential link function to map a conflict indicator into 14 severity index within safety continuum framework. Accident Analysis & Prevention. 2017 May 15 1:102:23-30. 16 41. Saunier N, Sayed T, Ismail K. Large-scale automated analysis of vehicle interactions and 17 collisions. Transportation Research Record. 2010 Jan;2147(1):42-50. 18 42. Ismail K, Sayed T, Saunier N. Methodologies for aggregating indicators of traffic conflict. 19 Transportation research record. 2011 Jan;2237(1):10-9. 20