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Using microsimulation to investigate the optimal deployment of leading pedestrian intervals at signalized intersections

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Abstract: The provision of leading pedestrian intervals (LPI) has emerged in recent years to achieve safety equitability for pedestrians at signalized intersections. LPI is a way to provide the pedestrian walk interval a few seconds before starting the circular green indication to adjacent parallel traffic. Although the safety benefit of LPI is indisputable, there are fundamental questions that need to be addressed for the optimal deployment of this strategy. First, can significant safety benefits for pedestrians be achieved while maintaining a satisfactory operational level of service for vehicles? Second, what are the application circumstances most conducive to achieving the greatest safety benefits for pedestrians? Third, how can a jurisdiction effectively assess contemplated treatments to achieve optimal deployment? This exploratory paper addresses these three fundamental questions by reviewing relevant literature before presenting the research from the application of microsimulation to fifteen Toronto intersections where LPIs have been implemented. The microsimulation involved using a recently released module for accommodating LPI phasing in the PTV Vistro software. To directly address the first and second questions, vehicle-to-pedestrian conflicts and vehicle delay were estimated for ten scenarios that allowed for the provision of, and variability in the LPI interval, right turn volumes, right turn on red provision, pedestrian and vehicle volumes, and crossing width. The results suggest that significant safety benefits can be achieved for pedestrians while maintaining a satisfactory level of service for vehicles. They further suggest that potential LPI deployments need to be assessed on a case-by-case basis since the effects of LPI can be significantly impacted by the influencing factors investigated. Statistical models were developed to quantify the effects of LPI implementation on vehicle-to-pedestrian conflicts after controlling for pedestrian and turning vehicle volumes. The results of this exploratory investigation, though interesting and consistent with the literature and logical considerations, may not be generalizable in a strict sense. Nevertheless, the study does provide a blueprint for investigating the design, traffic, and operational factors that can influence the impact of LPI on pedestrian safety without detrimentally impacting vehicle level of service.

Keywords: Leading Pedestrian Intervals, pedestrian safety, PTV Vistro, surrogate measures, traffic microsimulation, vehicle-to-pedestrian conflicts

1 Introduction

The National Highway Traffic Safety Administration (NHTSA), in 2019, disclosed that pedestrian fatalities have increased steadily since 2009 in the U.S. (NHTSA 2019). Therefore, it seems natural that pedestrian countermeasures feature prominently in Vision Zero programs in many cities in North America, and around the world for that matter. These countermeasures generally target the complex interactions between pedestrians and vehicles at signalized intersections. Leading Pedestrian Interval (LPI) is one such countermeasure. It has been proposed as a cost-efficient solution by providing a temporal separation between pedestrians and turning vehicles.

The LPI treatment provides the pedestrian walk interval a few seconds before the parallel vehicular green indication to adjacent traffic. Based on logical considerations and evidence from real-world studies, the safety benefit of LPI is undisputed. However, there are fundamental questions that need to be addressed to foster the optimal deployment of this strategy. First, can significant safety benefits for pedestrians be achieved while maintaining a satisfactory operational level of service for vehicles? Second, what are the LPI application circumstances most conducive to achieving the greatest safety benefits for pedestrians? Third, how can a jurisdiction effectively assess contemplated LPI treatments to achieve optimal deployment?

The paper addresses these three fundamental questions by reviewing relevant literature before presenting the research from the application of microsimulation to fifteen Toronto intersections where LPIs have been implemented. Microsimulation was selected as the method for this investigation over crash-based or video derived data analysis since (*a*) a prohibitively large database would be required to assess the application circumstances most conducive to achieving the greatest safety benefits, a problem that is exacerbated by the paucity of pedestrian crashes and high cost of video-derived data, and (*b*) microsimulation is most appropriate for evaluating safety and operational measures for scenarios that may be contemplated, but do not exist, as well as the effects of varying site characteristics such the length of the leading pedestrian interval and pedestrian and vehicle volumes.

The microsimulation involved the use of a recently released module for accommodating LPI phasing in the PTV Vistro software (Lynch n/d). The PTV Vistro implementation of LPI requires no additional signal phases to model exact LPI operations for the traffic controller, thereby facilitating LPI application in the software. The paper is organized as follows. In the next section, we review the literature related to the safety and operational effects of LPIs. The objectives and overview of the study are then presented. The fourth and fifth sections present the methodology and data used, followed by sections that analyze and discuss the results. A summary of the findings is presented in the final section, along with recommendations for future research.

2 Literature review

A Leading Pedestrian Interval (LPI) minimizes the conflicts between pedestrians and vehicles at signalized intersections by providing pedestrians with crossing time in advance. To do so, signal timing should be adjusted to allow pedestrians to cross a few seconds before starting the green time for vehicles (Saneinejad & Lo 2015). Although this operation is considered a cost-effective strategy for improving pedestrian safety, there can be a marked contrast between the safety effects from one location to another (Goughnour *et al.* 2021; Fayish & Gross 2010).

Fayish & Gross (2010) quantified the safety effects of LPI for ten signalized intersections in State College, Pennsylvania, using a 4 year before period and a 3 year after period. A reduction of 58.7% was estimated for pedestrian-vehicle crashes, with a 95% confidence interval between

46.2% and 71.3%. Pedestrian-vehicle crashes increased at the comparison sites during the same period. Although traffic and pedestrian volumes varied significantly from site to site and over the course of the day, all of the intersections had the same LPI interval of 3 seconds at all times. In addition to the safety evaluation, an economic analysis compared the mean comprehensive cost of pedestrian-vehicle crashes with the cost of implementing the LPI and determined that LPI was highly cost-effective. However, the likely increases in vehicle delay were not considered.

Another crash-based study was conducted by Goughnour *et al.* (2021), who used data from 56 treated intersections in Chicago, 42 treated sites in New York City, and 7 treated sites in Charlotte, North Carolina to evaluate the safety effect of LPI. The crash modification factor (CMF) for pedestrian-vehicle crashes for all cities combined was 0.87 (a reduction of 13%), which was significant at a 95-percent confidence level. Interestingly, New York City entirely prohibited right turn on reds (RTORs) at treated sites, while Chicago allowed this movement in most cases.

Other studies evaluated LPI based on traffic conflicts as crash surrogates. These included Hubbard *et al.* (2008), who evaluated the safety impacts of LPI using traffic conflict data derived from the recorded video at suburban intersections. For this, pedestrians were categorized as compromised or non-conflicting. A compromised pedestrian was defined as a situation in which the pedestrian is delayed because of a turning vehicle or changes their travel path or speed, while non-conflicting pedestrians can cross without any interruption from turning vehicles. Their results suggest that LPI could not improve pedestrian safety in the suburban environment without prohibiting right turn on red (RTOR). They observed that pedestrian crossings conflicting with right-turn vehicles during the walk interval increased after implementing LPI. Moreover, they found, perhaps logically, that the right-turn volume is a key indicator of the effect of LPI, so much so that restricting RTOR with LPI implementation was proposed to improve the safety efficiency of LPI.

In another study based on video-derived traffic conflict data, Guo *et al.* (2020) evaluated the safety effect of LPI using a hierarchical Bayesian peak over threshold (POT). The results indicated a reduction of between 18.1% and 20.9% in severe vehicle-to-pedestrian conflicts based on post encroachment time (PET). They suggested considering the influence of factors such as road condition, pedestrian volume, left-turn traffic volume, and different values of LPI intervals for future research since they could not incorporate these factors in their model. Interestingly, severe vehicle-to-pedestrian conflicts were proposed as a more realistic indicator of safety effects, an approach that is becoming increasingly popular (Cavadas *et al.* 2020; Zheng & Sayed 2019; Zheng *et al.* 2014).

Operational effects, such as increased vehicle queues and delays because of lost green time to accommodate the LPI, are to be expected logically. Among the more prominent studies considering operational impacts of LPI is one by Saneinejad & Lo (2015), who proposed a suitability assessment checklist for LPI in the City of Toronto that considers the impact of this treatment on vehicular delay and level of service. They indicated that LPI has a negative effect on capacity and delay at intersections with high turning volumes. For one such intersection, for example, the total intersection delay increased by 20% in morning peak hour and 26% in afternoon peak hour. Moreover, the through phase volume to capacity (V/C) ratio of the intersection with LPI implemented reached 0.94 and 0.75, respectively, for the morning and afternoon peak periods.

Few studies have considered safety and operational benefits of LPI in combination. Most cited of these is one by Sharma *et al.* (2017), who considered the costs (delay) and benefits (safety) of LPI using quantitative metrics to examine the success of implementing an LPI at specific signalized intersections. They offered a guideline on whether or not to use an LPI at an intersection based on turning movement volumes, the number of crashes, and geometry. Calculating crash numbers for each scenario was complicated in that it considered the actual traffic condition and a probabilistic function. To predict the crash reduction based on each scenario, they used right-turning and pedestrian volumes and calculated the probability of the simultaneous presence of at least one vehicle and a pedestrian during the same right of way at the onset of green. Then, by comparing pedestrian crash reduction cost and additional vehicle delay cost, a determination could be made on whether the treatment is cost-beneficial or not.

In sum, the literature review confirmed the need for a study such as the current one in that it indicated that there is precious little consistent information on the influence of site features and LPI implementation circumstances on both the safety and operational effects of LPIs. In addressing that need, we investigate whether significant safety benefits for pedestrians can be achieved while maintaining a satisfactory operational level of service for vehicles. In so doing, we provide a blueprint on how a jurisdiction can effectively assess contemplated treatments to achieve optimal deployment.

3 Study objectives and overview

This study is an exploratory one that aimed to address the need for more information on the influence of site features and LPI implementation circumstances on both safety and operational effects of LPIs. At the same time, the intent was to provide a blueprint for jurisdictions to undertake such assessments in optimizing the deployment of contemplated LPI installations. Microsimulation was selected as the tool for this investigation since it is most appropriate for evaluating safety and operational measures for multiple scenarios that may be contemplated, but do not exist. It is especially where there is very limited availability of crash data and crash modification factors, as is the case for pedestrian measures. Microsimulation was used to estimate delay, and vehicle-to-pedestrian conflicts for two scenarios at fifteen Toronto intersections – one with LPI implemented and one before LPI implementation. For one of these intersections, a similar evaluation was done for eight more hypothetical scenarios that were defined based on indications from previous studies to examine the potential influence of factors such as turning volumes, crossing width, length of the LPI interval, pedestrian volumes, and whether or not right turn on red (RTOR) is allowed. Detailed descriptions of each scenario are presented later in the paper (Table 4).

4 Methodology

The methodological framework is presented in Figure 1. The vehicular delay incurred due to an LPI implementation was measured by creating a layout in PTV Vistro containing all relevant parameters, including vehicles, pedestrians, and signal timing. Using this software, the Level of Service (LOS), vehicle delay, and maximum queue length can be calculated for each scenario. Level of Service (LOS) indicates the quality of traffic operations at an intersection, ranging from LOS A to LOS F, with LOS A indicating little or no traffic delays and LOS F indicating poor operation with very long delays. As noted earlier, the PTV Vistro implementation of LPIs requires no additional signal phases to model exact LPI operations for the traffic controller, thereby facilitating LPI application in the software. In Vistro, LPI can be mimicked by utilizing the 'Delayed Vehicle Green' parameter. Then, in order to measure the number of conflicts, PTV VISSIM was first used to develop a simulation of pedestrians and vehicles for each scenario using the intersection file developed on PTV Vistro. Second, the Surrogate Safety Assessment Model (SSAM) (FHWA 2008; Pu & Joshi 2008) was applied to automatically identify, classify, and evaluate pedestrian-vehicle conflicts from the VISSIM trajectory output. It is worth mentioning that it was not possible to calibrate VISSIM for this study since there was no ground truth data. Earlier research (Saleem *et al.* 2014) based on Toronto signalized intersection data found that using VISSIM with pre-calibrated default model parameter values to estimate conflicts, gave comparable results in relating conflicts to crashes generated with parameter values endogenously estimated. After identifying the number of severe vehicle-to-pedestrian conflicts, a deep learning method called autoencoder neural network was used to label the subset of extremely severe vehicle-to-pedestrian conflicts (anomalies) (Olive & Basora 2020; Tejada *et al.* 2020; Fernández *et al.* 2019; Olive & Basora 2019; Olive & Grignard 2018) based on the conflicts reported from SSAM.

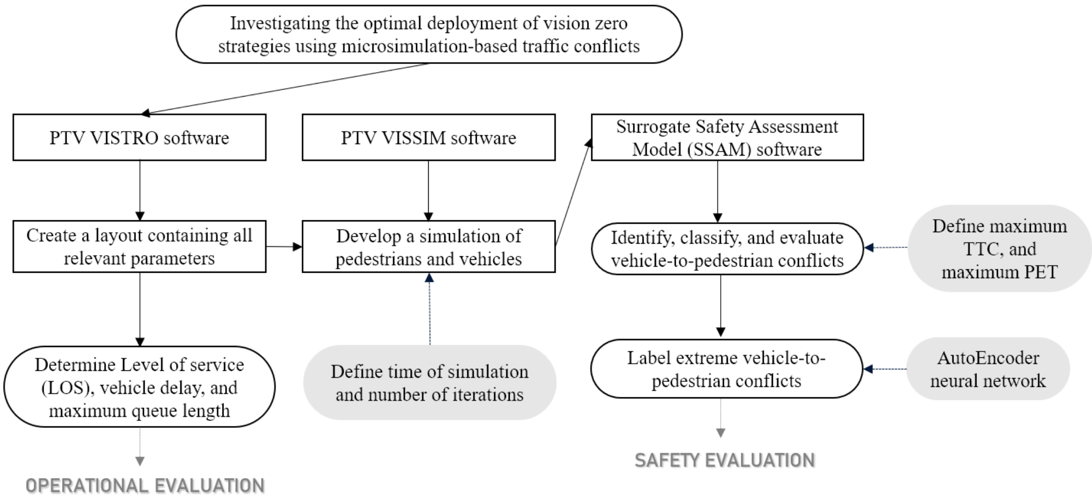

Figure 1 **Methodological framework**

Each simulation run lasted for one hour in PTV VISSIM, and ten simulation runs were done for each scenario. SSAM identified simulated conflicts based on threshold values of two surrogate safety measures illustrated in Figure 2: the maximum time to collision (TTC), and the maximum post encroachment time (PET). As originally defined by Hayward (1972), TTC is '…the time that remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained'. PET measures situations in which two road users are not on a collision course and, as defined by Allen *et al.* (1978), 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. Lower (or higher) TTC or PET values represent a shorter (or longer) time to collide and a higher (or lower) probability of more severe collisions.

To identify conflicts, a TTC threshold of 2s is usually used, but a TTC between 1.6 and 2 is considered to have a low collision risk (Sayed & Zein 1999). Therefore, it was decided to use a maximum TTC threshold of 1.5 seconds and a maximum PET threshold of 1.5 seconds to capture those severe conflicts that are more likely to be surrogates for crashes (Milosavljevic 2018; Tageldin & Sayed 2016).

Conflicts so obtained, using TTC and PET thresholds of 1.5 seconds, are referred to hereafter as 'severe' conflicts to distinguish them from the subset of 'extremely severe' conflicts obtained with the autoencoder model. The average over the ten runs of the number of vehicle-to-pedestrian conflicts was used.

The final part of the analysis was the development of statistical models to quantify the effects of LPI implementation on pedestrian-vehicle conflicts after controlling for pedestrian and turning vehicle volumes. Two sets of conflicts were modelled – the 'severe' ones identified from the SSAM software with maximum TTC threshold of 1.5 seconds and maximum PET threshold of 1.5 seconds, and the subset of 'extremely severe' ones identified using the autoencoder technique.

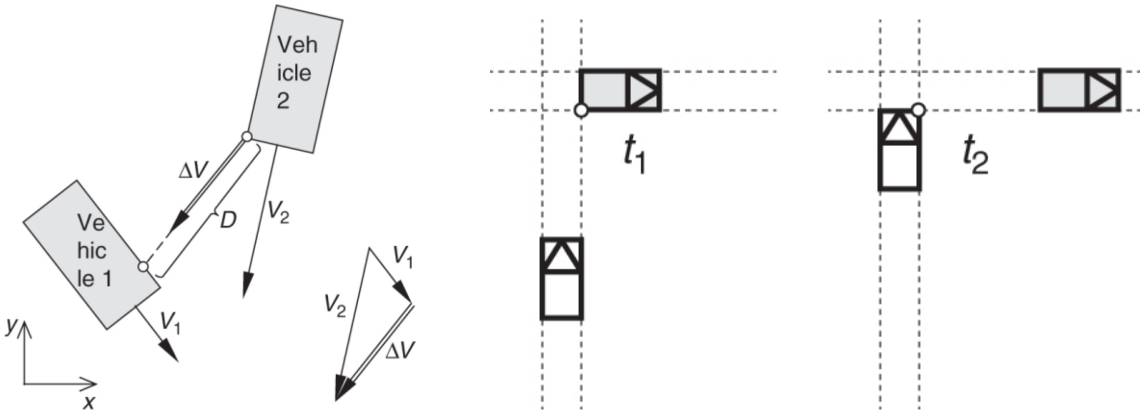

Figure 2 **TTC (left), adopted from (Hayward 1972), and PET (right), adapted from (Allen *et al.* 1978)**

The use of extremely severe conflicts not only overcomes the low sample size issue for pedestrian crashes, but it also logically provides a more realistic surrogate for crashes compared to the universe of severe vehicle-to-pedestrian conflicts based on some arbitrary threshold (Guo *et al.* 2020). Of late, one of the most common tools used for estimating extremely severe conflicts is autoencoders (Olive & Basora 2020; Tejada *et al.* 2020; Fernández *et al.* 2019; Olive & Basora 2019; Olive & Grignard 2018). A single-layer autoencoder neural network anomaly detection algorithm is illustrated in Figure 3. Encoding and decoding work in the latent space and minimize the mean reconstruction loss during the training process. Due to the relatively low frequency of anomalies (i.e., extreme conflicts) in the training samples, the autoencoder does not prioritize their reconstruction while training. Thus, it can easily determine if a reconstruction error exceeds the anomaly decision threshold by comparing the original indicators (e.g. input) with the reconstructed ones (e.g. output) (Fernández *et al.* 2019).

These key advantages of this algorithm include learning the inherent data characteristics that distinguish safe events from anomalous or unsafe events without requiring labelled data, and the ability to work with multidimensional data (Tejada *et al.* 2020). Thus, it seems natural that autoencoders provide an ideal technique for detecting extremely severe vehicle-to-pedestrian conflicts.

The basic principle of an autoencoder can be seen by considering a training data set $\{x_1, x_2, \dots, x_N\}$ where N is the size of the training data and $x \in \mathbb{R}^d$. An autoencoder training problem is then solved by optimizing:

$$min \sum_{i=1}^{N} \|x_i - \hat{x}_i\|^2 \tag{1}$$

where $\hat{x}_i$ represents a reconstructed interaction corresponding to x_i as an input or original interaction.

In the application in this study, the conflict classification process included (*a*) randomly split test and train subsets, 20% and 80%, respectively (*b*) running an autoencoder neural network utilizing TTC and PET indicators, (*c*) labelling each conflict with a unique anomaly score, and (*d*) classifying extremely severe conflicts by testing different anomaly score thresholds. Figure 4 plots the autoencoder reconstruction error distribution for 15 intersections in the city of Toronto. This histogram provides a continuous reconstruction error distribution for each data sample that helps identify the anomaly decision threshold. A sharp decrease in the distribution suggests that the anomaly decision threshold should be close to that value. The conflicts that exceed the threshold are labeled as extremely severe ones. In Figure 4, the blue line represents the anomaly score, and the red rectangle suggests the potential threshold area.

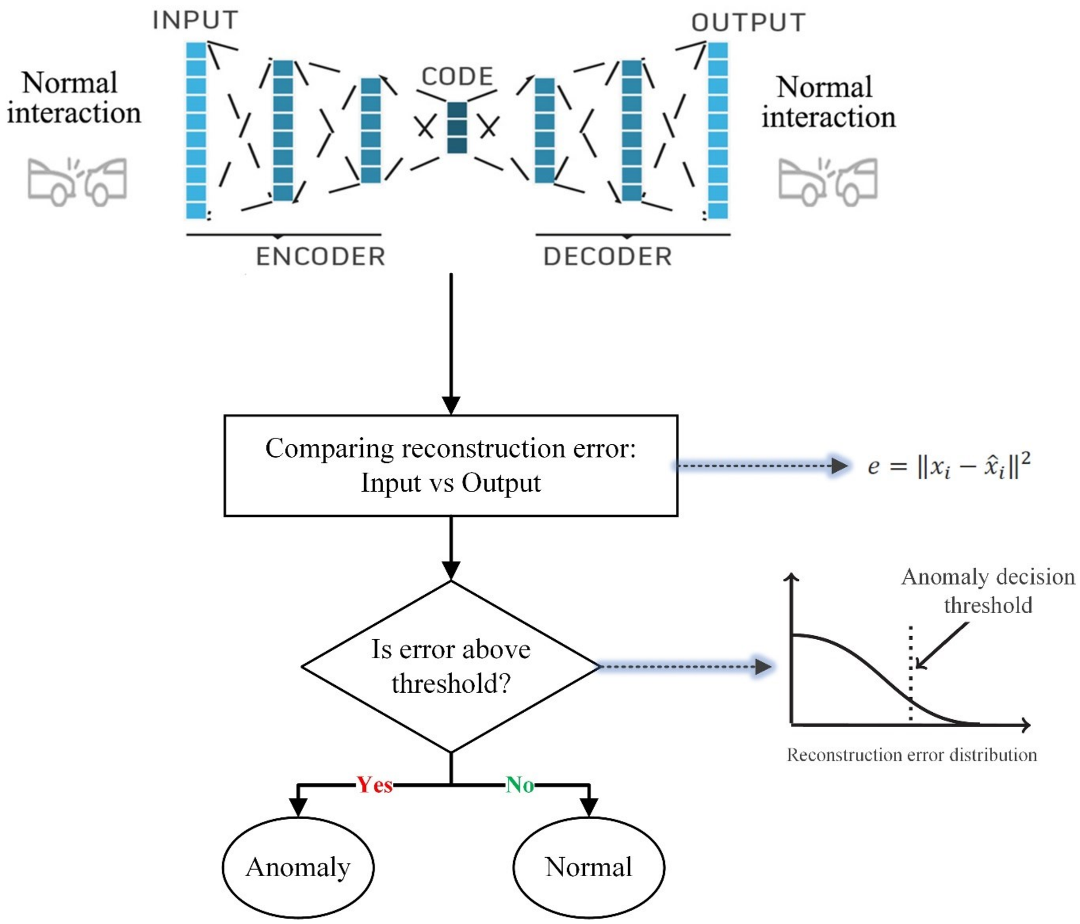

Figure 3 **Anomaly detection using autoencoder neural network, adapted from (**Fernández *et al.* 2019**)**

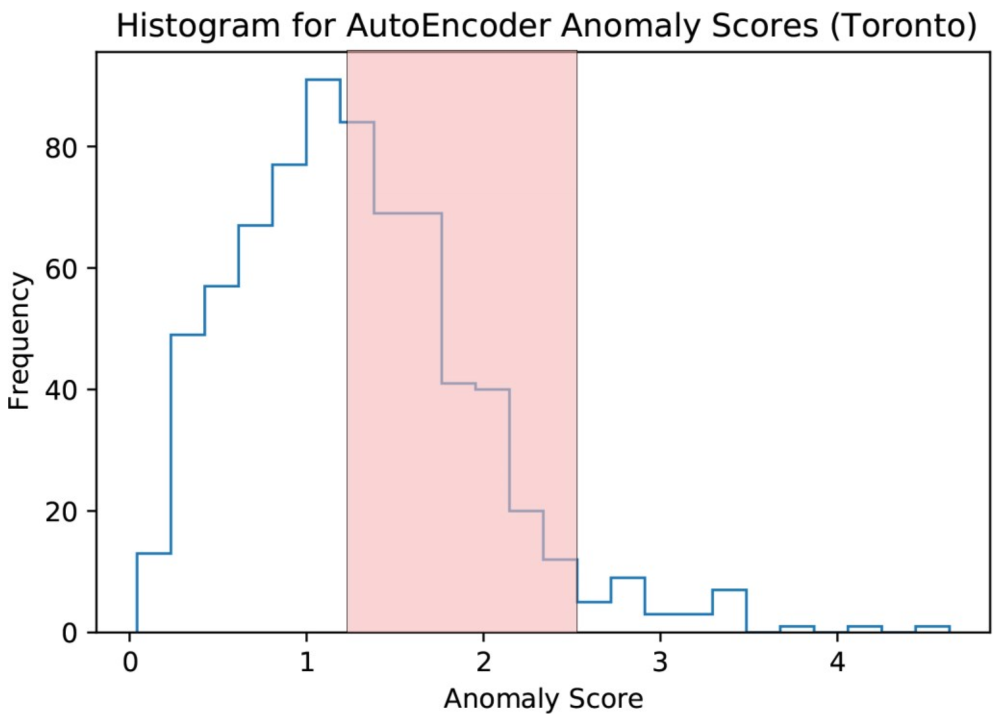

Figure 4 **Histogram of outlier scores obtained from autoencoder algorithm**

5 Data description

It was decided to conduct the exploration at City of Toronto intersections with a range of pedestrian volumes, where LPI has been integrated into the signal timing. Fifteen such intersections were selected for the analysis. Figure 5 shows the selected intersections, as well as Google map images for a sample of 4 intersections. 15-minute traffic volumes at intersections were extracted from the Toronto Transportation Services Division open-source data portal; this allowed for the peak hour to be identified and the traffic volumes to be estimated for the simulations. Table 1 summarizes the vehicle and pedestrian volume data for the analyzed intersections. The traffic data included different vehicle types, including passenger cars, trucks, and buses.

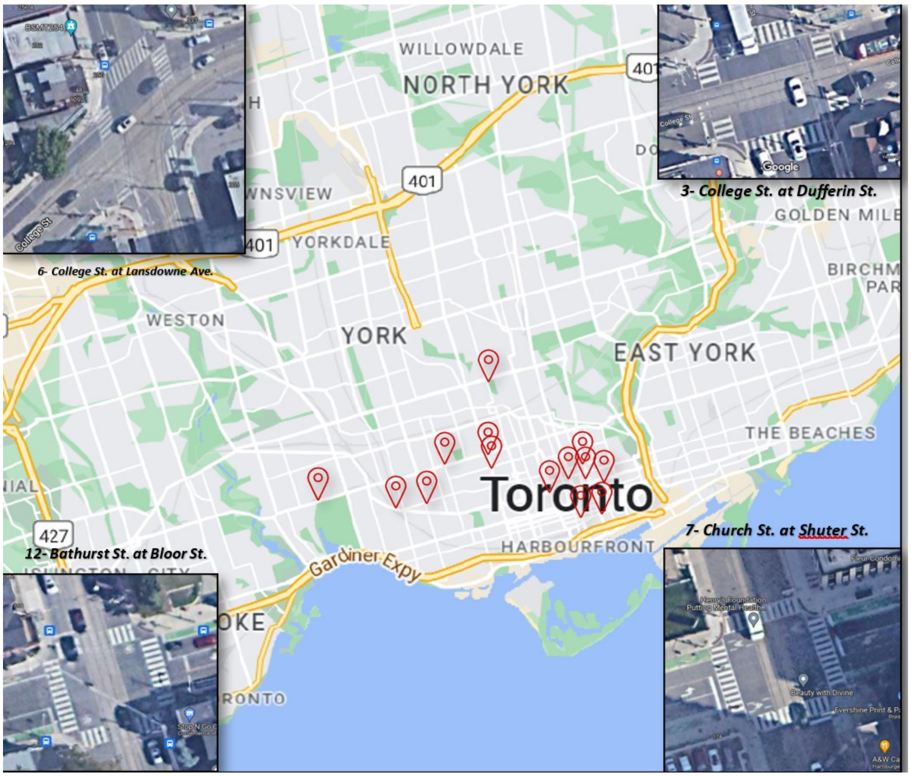

Figure 5 **Study area**

The LPI duration for all intersections was set by the City of Toronto as 5 seconds. However, for this research, one scenario was defined to evaluate the safety and operational changes for a different LPI duration of 3 seconds that has been used in other jurisdictions. All intersections had ‘permissive-only’ left-turn phasing. For all but two of the intersections, right turn on red (RTOR) is permitted.

6 Analysis, results, and discussion

6.1 Combined results for vehicle-to-pedestrian conflicts and vehicle delay

Table 2 shows vehicle delay and Level of Service (LOS), along with severe vehicle-to-pedestrian conflicts, as well as the subset of extremely severe ones for the fifteen intersections analyzed without LPI implementation and with full LPI implementation (for all 4 Directions). Cycle length was assumed to remain the same with or without LPI implementation. Vehicle Level of Service is reported based on the estimated delay for each scenario. The % changes (reductions) in conflicts and % changes (increases) in vehicle delay after full LPI implementation are shown in parentheses in columns 6 to 8. As seen in Table 2, vehicle delay increased after LPI was implemented, while the number of vehicle-to-pedestrian conflicts generally decreased. Of special note is the fact that, despite the tangible increase in delay, the Level of Service post-LPI is still at an acceptable level for 12 of the 15 intersections (i.e. 'C' or 'D'). However, there is substantial variation in the effects for the number of vehicle-to-pedestrian conflicts, suggesting that influencing factors may be at play. To illustrate, at the Church and Dundas intersection, a modest safety improvement was experienced after implementing LPI, with about a 32% reduction for severe conflicts and a 6% reduction for extremely severe conflicts. On the other hand, at the Church and Gerrard intersection, pedestrian safety improved substantially after implementing LPI, with reductions of 67% and 50% in severe and extremely severe conflicts, respectively.

Table 1 **Summary data on peak hour volumes (veh/h) for the selected intersections**

		Northbound	**Southbound**	**Eastbound**	**Westbound**
Through traffic volume	Minimum	172	138	18	15
	Average	453	509	271	341
	Maximum	692	1 075	599	618
Left-turn volume	Minimum	0	1	36	3
	Average	36	60	56	46
	Maximum	83	109	105	150
Right-turn volume	Minimum	29	37	29	20
	Average	69	78	48	64
	Maximum	126	138	76	107
Outbound pedestrian volume crossing major street	Minimum	23	21	23	17
	Average	124	141	119	144
	Maximum	228	516	268	389
Inbound pedestrian volume crossing major street	Minimum	23	17	23	21
	Average	119	144	124	141
	Maximum	268	389	228	516
Outbound pedestrian volume crossing minor street	Minimum	28	24	25	26
	Average	106	120	120	105
	Maximum	259	225	231	207
Inbound pedestrian volume crossing minor street	Minimum	26	25	24	28
	Average	105	120	120	106
	Maximum	207	231	225	259

6.2 Estimation of statistical models for vehicle-to-pedestrian conflicts

The objective here was to use the estimated severe and extremely severe vehicle-to-pedestrian conflicts to quantify the effects of LPI implementation after controlling for pedestrian and turning vehicle volumes. Generalized linear models with a negative binomial error structure and a form similar to that used for crash frequency models were estimated using SAS Enterprise Guide 7.1 (Meyers *et al.* 2009).

Table 2 **Delay and vehicle-to-pedestrian conflicts with and without LPI at 15 intersections**

	Intersection name	LPI Presence	Cycle Length [s]	Vehicle LOS	Vehicle Delay [s/veh]	Severe vehicle-to-pedestrian conflicts [con/h] TTC=< 1.5 and PET=< 1.5	Extremely severe conflicts [con/h]
1	Church st at Gerrard st (px 22)	NO	70	B	18.72	39	0.4
		YES		D	37.60 (+101%)	13 (-67%)	0.2 (-50%)
2	Lower Jarvis St at the Esplanade (px 1392)	NO	75	B	15.69	49	0.5
		YES		C	21.47 (+37%)	13 (-73%)	0.5 (0%)
3	College st at Dufferin st (px 605)	NO	80	B	17.79	47	2.5
		YES		C	23.60 (+33%)	25 (-47%)	1.3 (-48%)
4	Bloor st at Runnymede rd (px 331)	NO	98	C	28.08	28	2
		YES		D	44.22 (+57%)	26 (-7%)	0.8 (-60%)
5	Dundas st at Jarvis st (px 8)	NO	76	C	20.46	32	1
		YES		C	32.45 (+59%)	22 (-31%)	0.5 (-50%)
6	College st at Lansdowne ave (px 831)	NO	90	C	27.73	10	0.2
		YES		D	41.02 (+48%)	1 (-90%)	0
7	Church st at Shuter st (px 20)	NO	76	B	17.06	26	0.4
		YES		C	22.29 (+31%)	13 (-50%)	0.2 (-50%)
8	Bloor st at Dovercourt rd (px 324)	NO	100	C	30.41	30	0.4
		YES		E	58.13 (+91%)	13 (-57%)	0.2 (-50%)
9	Church st at Dundas st (px 21)	NO	76	D	38.75	84	1.7
		YES		E	71.67 (+85%)	57 (-32%)	1.6 (-6%)
10	Bathurst st at Harbord st (px 303)	NO	80	C	23.79	22	0.3
		YES		D	37.71 (+59%)	8 (-64%)	0.4 (-33%)
11	Queen st e & Church (px 19)	NO	90	C	23.45	131	3.9
		YES		D	53.98 (+130%)	48 (-63%)	2.1 (-46%)
12	Bathurst st at Bloor st (px 321)	NO	90	C	21.63	27	1.4
		YES		C	27.23 (+26%)	20 (-26%)	0.6 (-57%)
13	Queen st at Victoria st (px 28)	NO	90	B	16.42	131	2.6
		YES		C	22.01 (+34%)	62 (-53%)	1.3 (-50%)
14	Elm st at University ave (px 82)	NO	84	B	18.91	13	0
		YES		F	84.86 (+349%)	2 (-85%)	0
15	Heath st at Spadina rd (px 1 376)	NO	80	C	20.66	6	0.5
		YES		C	27.90 (+35%)	2 (-67%)	0

Four models were developed, as described below, with Models 1 to 3 based on severe conflicts and Model 4 on extremely severe conflicts.

Model 1 (equation (2)) was developed using the summation of the pedestrian crossing volume and vehicle turning volume as the exposure variable. The γ_1 are the regression coefficients applied where LPI is present and N_i is the expected number of vehicle-to-pedestrian conflicts per hour for intersection i:

$$N_i = e^{\alpha_1} \times \text{Exposure}^{\beta_1} \times e^{\gamma_1\{\text{with } LPI\}}. \tag{2}$$

The exposure variable for Model 2 (equation (3)) is the product of the pedestrian crossing and vehicle turning volume, and, as before, the γ_1 are the regression coefficients applied where LPI is present:

$$N_i = e^{\alpha_1} \times \text{Exposure}^{\beta_1} \times e^{\gamma_1\{\text{ with } LPI\}}. \tag{3}$$

Model 3 (equation (4)), which, like Model 2, also uses as exposure the product of the pedestrian and vehicle turning volumes, was estimated to examine if pedestrian volume impacts the effect of LPI:

$$N_i = e^{\alpha_1} \times \text{Exposure}^{\beta_1} \times e^{\gamma_1\{\, LPI\ Category\ 1\}} e^{\gamma_2\{\, LPI\ Category\ 2\}}. \tag{4}$$

The *k*-mean clustering algorithm (Nwanganga & Chapple 2020) was used to separate high and low pedestrian volumes (e.g. categories 1 and 2 in equation (4)). This algorithm employs an iterative approach to group the data into a pre-determined k number of clusters (i.e., 2 clusters) and randomly picks k positions as initial cluster centers such that each data point belongs to the closest cluster. This procedure is repeated until optimum convergence is achieved. As illustrated in Figure 6, the optimum clustering result was obtained with a 'random' selection of initial cluster centers, 300 iterations, and the 'elkan' *k*-means algorithm, which consists of two categories with a separation point of a pedestrian volume of 1161. The gray points in Figure 6 depict the cluster centers, and two colors are used to differentiate the clusters:

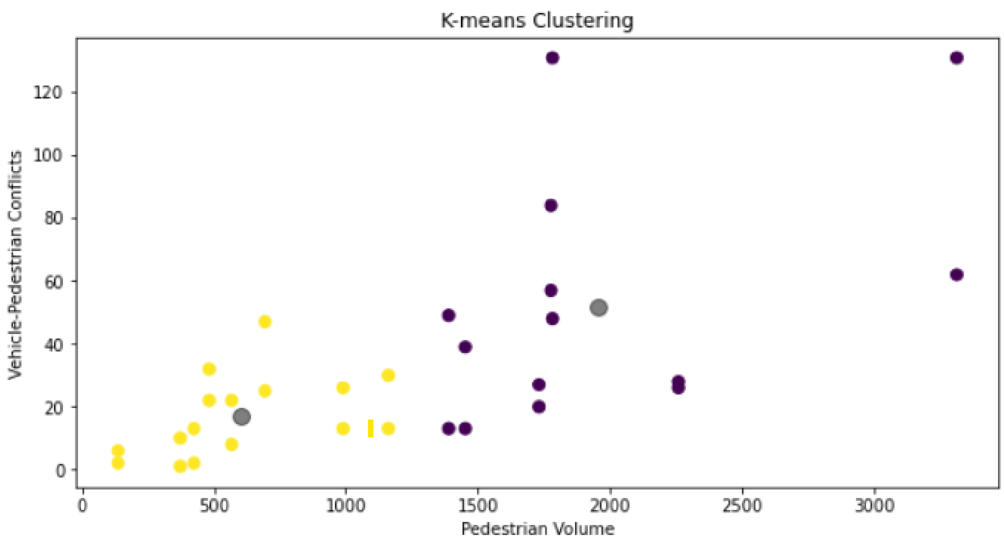

Figure 6 ***k*-means clustering result**

Model 4 (equation (5)) was based on extremely severe vehicle-to-pedestrian conflicts (last column of Table 2) as the dependent variable:

$$N_i = e^{\alpha_1} \times \text{Exposure}^{\beta_1} \times e^{\gamma_1\{\text{with } LPI\}}. \tag{5}$$

Therefore, for this model, N_i is the expected number of extremely severe vehicle-to-pedestrian conflicts per hour per intersection. Similar to Model 1, the summation of the pedestrian crossing and turning vehicle volume was applied as the exposure variable. The γ_1, as before, are the regression coefficients applied where LPI is present.

The modeling results are shown in Table 3. In general, the estimated effects for all variables in terms of direction are consistent with logic and previous research findings. For example, more pedestrian and vehicle turning volumes are associated with more vehicle-pedestrian conflicts. And LPI implementation is associated with reduced conflicts. The p-values for all variables in all models were estimated to be highly significant, indicating a reasonable statistical fit for each model. Model 1 is better than Model 2 in terms of the lower dispersion parameter, AIC, and BIC. The Cumulative Residual (CURE) plots in Figure 7 confirm the superiority of Model 1 in that the residuals consistently oscillate around the x-axis, and there are no extended ranges of over or under-prediction.

Table 3 **GLM model results for vehicle-pedestrian conflicts**

	Model 1		**Model 2**		**Model 3A**		**Model 3B**		**Model 4**	
Parameter	**Est.**	***p*-value**	**Est.**	***p*-value**	**Est.**	***p*-value**	**Est.**	***p*-value**	**Est.**	***p*-value**
Intercept	-5.93	0.0002	-7.49	<.0001	-9.94	0.1863	-5.28	0.1562	-16.34	< .0001
Ln (Pedestrian Crossing Volume + Turning Volume)	1.31	< .0001	-	-	-	-	-	-	1.19	0.0002
Ln (Pedestrian Crossing Volume * Turning Volume)	-	-	0.87	< .0001	1.05	0.0598	0.68	0.0242	-	-
With LPI Implementation	-0.76	0.0005	-0.76	0.0006	-	-	-	-	-0.65	0.0387
With LPI Implementation and high pedestrian volume	-	-	-	-	-0.76	0.0090	-	-	-	-
With LPI Implementation and low pedestrian volume	-	-	-	-	-	-	-0.76	0.0207	-	-
Dispersion Parameter		0.30		0.31		0.27		0.36		0.58
Akaike's information criterion (AIC)		249.75		250.55		135.37		122.31		190.16
Bayesian information criterion (BIC)		255.35		256.15		137.93		125.40		195.76

For Model 3, the estimates of the parameter γ_1 are identical for the higher volume (Model 3A) and γ_2 for lower volume (Model 3B) categories, indicating that pedestrian volume does not materially influence the effect of LPI. Based on this outcome, it can be concluded that Model 1, which combines the two pedestrian volume categories, is also preferred over Model 3. Given this preference, the form of the exposure term for Model 1 was also used for Model 4. The estimated coefficient in Model 1 for LPI implementation suggests a reduction in severe conflicts of $[100 \cdot (1 - \exp(-0.76)] = 53\%$, approximately. This is of the same order as the reduction in extremely severe conflicts, $[100 \cdot (1 - \exp(-0.65)] = 48\%$. Considering the recent crash modification factor (CMF) estimate of 0.87 (Goughnour *et al.* 2021), these numbers would imply that a 10% reduction in pedestrian conflicts would be associated with a 2% reduction in crashes. Although there are no available crash prediction models for vehicle-pedestrian conflicts, there can be some assurance that these effects are reasonably consistent with indications from crash prediction models currently available for vehicle-vehicle conflicts (Peesapati *et al.* 2018; Saleem *et al.* 2014).

It should be stressed that these models are simply exploratory, given that the data are very limited, especially for Model 4, which is arguably the most useful model, but has the largest overdispersion parameter. The results nevertheless indicate that quantifying the effects of influencing factors is feasible for a full investigation with larger sample sizes. Such an investigation would consider using separate terms for vehicle and pedestrian volumes, alternative model forms, and the inclusion of other influencing factors found in this research to be pertinent.

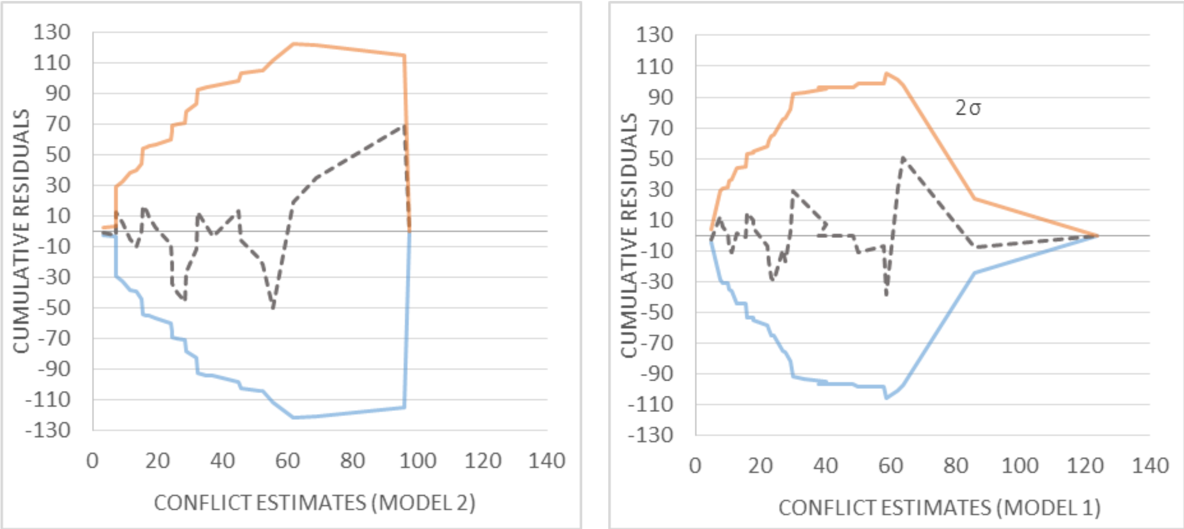

Figure 7 **CURE plots for vehicle-to-pedestrian conflict model estimates**

6.3 Evaluation of influencing factors

As mentioned earlier, eight additional scenarios were investigated for one intersection (Church and Gerard) having a high pedestrian volume during morning peak hours to gain insights into the effects of influencing factors on safety and operational impacts. Information on these scenarios, as well as the two originally investigated (#1 and #10), is presented in Table 4.

Table 4 **Definition of scenarios explored for Church and Gerard intersection**

	LPI characteristics	Change in pedestrian volume	Change in right turn volume	Change in left turn volume	Change in through volume	Right turn on red	Change in lane width
Scenario 1 (original)	EW-5 seconds	0	0	0	0	Allowed	0
Scenario 2	EW-5 seconds	0	20%	0	0	Allowed	0
Scenario 3	EW-5 seconds	0	0	20%	0	Allowed	0
Scenario 4	EW-5 seconds	0	0	0	10%	Allowed	0
Scenario 5	EW-5 seconds	0	0	0	0	Prohibited	0
Scenario 6	EW-5 seconds	0	0	0	0	Allowed	10%
Scenario 7	EW-3 seconds	0	0	0	0	Allowed	0
Scenario 8	EW & NS-5 seconds	0	0	0	0	Allowed	0
Scenario 9	EW-5 seconds	20%	0	0	0	Allowed	0
Scenario 10	No LPI	0	0	0	0	Allowed	0

Table 5 shows vehicle delay and level of service (LOS), total severe vehicle-to-pedestrian conflicts, as well as extremely severe vehicle-to-pedestrian conflicts for the Church and Gerrard intersection based on all 10 scenarios identified in Table 4. In addition, Table 5 expresses the results as percent changes in delay and conflicts for Scenarios 1 to 9 compared to Scenario 10 (in parentheses). Furthermore, severe vehicle-to-pedestrian conflicts are reported for three different thresholds combinations for TTC and PET that are based on investigations by other researchers. For example, in Wu et al., the TTC parameter was set at 2.7 seconds and the PET was set at 8 seconds (Wu *et al.* 2017), while in (Milosavljevic 2018; Tageldin & Sayed 2016) a maximum TTC threshold of 1.5 seconds and a maximum PET threshold of 1.5 seconds were used.

Table 5 **Delay and vehicle-to-pedestrian conflicts for ten scenarios at the Gerrard and Church intersection (% change compared to Scenario 10 in parentheses)**

	Vehicle LOS	Vehicle delay [s/veh]	Severe vehicle-to-pedestrian conflicts (TTC ≤ 2.7 & PET ≤ 8)	(TTC ≤ 1.5 & PET ≤ 8)	(TTC ≤ 1.5 & PET ≤ 1.5)	Extremely severe vehicle-to-pedestrian conflicts
Scenario 1	C	32.00 (+71%)	44 (-6%)	40 (-7%)	37 (-5%)	0.50 (+25%)
Scenario 2	C	33.45 (+79%)	46 (-2%)	42 (-2%)	39 (0%)	0.40 (0%)
Scenario 3	C	32.75 (+75%)	40 (-15%)	37 (-14%)	33 (-15%)	0.30 (-25%)
Scenario 4	D	39.19 (+109%)	45 (-4%)	41 (-5%)	39 (0%)	0.50 (+25%)
Scenario 5	D	41.08 (+119%)	33 (-30%)	29 (-33%)	27 (-31%)	0.60 (+50%)
Scenario 6	C	31.73 (+69%)	48 (+2%)	45 (+5%)	40 (+3%)	0.80 (+100%)
Scenario 7	C	23.59 (+26%)	52 (+11%)	48 (+12%)	45 (+15%)	0.80 (+100%)
Scenario 8	D	37.60 (+101%)	18 (-62%)	15 (-65%)	13 (-67%)	0.20 (-50%)
Scenario 9	C	32.14 (+72%)	56 (+19%)	51 (+19%)	46 (+18%)	0.60 (+50%)
Scenario 10	B	18.72	47	43	39	0.40

Several observations can be made from the results in Table 5:

- Providing LPI for both approaches (E.W. and N.S.) (Scenario 8) has the largest impact of all changes considered in isolation. There are substantial reductions in severe and extremely severe conflicts, accompanied by an increase in delay which, nevertheless, still results in a tolerable LOS.
- Increased crossing distance (Scenario 6) results in, approximately, a 3% increase in severe conflicts, a 100% increase in extremely severe ones, and a 69% increase in delay.
- Prohibiting RTOR (Scenario 5) could decrease severe conflicts but increase extremely severe ones. There is an increase in delay which, nevertheless, still results in a tolerable LOS.
- For two scenarios, severe conflicts and extremely severe ones show different trends. Prohibiting RTOR (Scenario 5) decreased vehicle-to-pedestrian conflicts but increased the extremely severe vehicle-to-pedestrian conflicts. Moreover, for Scenario 1 (providing LPI for E-W direction only), extremely severe conflicts trends did not follow the logical trend, which may be because the extremely severe conflicts are intuitively rare; in addition, each simulation iteration ran for only one hour, so that more simulation time may resolve the apparent anomaly.

In summary, the results illustrate the order and direction of the effects of the influencing factors for pedestrian safety and delay with LPI implementations, namely, left-turn volume, RTOR prohibition, crossing width, duration of LPI, number of approaches with LPI implemented, and pedestrian volume.

7 Conclusions and further work

This study provided a blueprint for using microsimulation-derived traffic conflicts to investigate the design, traffic, and operational factors that can influence the impact of LPI on pedestrian safety without detrimentally impacting vehicle level of service. The results suggest that LPI can yield significant safety benefits for pedestrians while maintaining a satisfactory level of service for vehicles. They further indicate that potential LPI deployments need to be assessed on a case-by-case basis, as the effects of LPI can be significantly impacted by influencing factors such as left-turn and right-turn volumes, RTOR prohibition, crossing width, duration of LPI, number of approaches with LPI implemented, and pedestrian volume. The paper illustrates that such case-by-case assessments, using state-of-the-art software, are doable and can be valuable for optimizing the deployment of such strategies.

Statistical models were developed to use estimated severe and extremely severe vehicle-to-pedestrian conflicts to quantify the effects of LPI implementation on pedestrian-vehicle conflicts after controlling for pedestrian and turning vehicle volumes. These models indicated 53% and 48% reductions in severe and extremely severe conflicts, respectively. Considering the most recent crash-based CMF estimate of 0.87 by Goughnour *et al.* (2021), these numbers would imply that a 10% reduction in pedestrian conflicts would be associated with a 2% reduction in crashes. Although there are no available crash prediction models for vehicle-pedestrian conflicts, there can be some assurance that these effects are reasonably consistent with indications from crash prediction models currently available for vehicle-vehicle conflicts (Peesapati *et al.* 2018; Saleem *et al.* 2014).

The practical application benefits of the research lie in its contribution to evaluating the economic and operational impacts of LPI installation. Specifically, economic impacts can be optimized by identifying practical application circumstances to achieve the maximum safety benefit for pedestrians at a satisfactory operational Level of Service for vehicles.

The results from this exploratory study, though promising and consistent with the literature (Goughnour *et al.* 2021; Milosavljevic 2018; Sharma *et al.* 2017; Saneinejad & Lo 2015) and logical considerations, are not generalizable in a strict sense. They do suggest, however, that quantifying the effects of influencing factors is feasible for a full investigation that would consider using alternative model forms, larger sample sizes and the inclusion of other influencing factors. As such, further work could evaluate a larger sample and perhaps a wider variety of intersections and scenarios to make the results more generalizable and facilitate the further development of the statistical models. Such research can be complemented by a case-control methodological approach applied to pedestrian crash data to identify factors that influence pedestrian crash occurrence at intersections with and without LPI. Considering the paucity of such data, it may be informative to further explore the extremely severe conflicts.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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