Are Signalized Intersections with Cycle Tracks Safer? A Case-Control Study Based on Automated Surrogate Safety Analysis using Video Data

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ABSTRACT

Cities in North America have been building bicycle infrastructure, in particular cycle tracks, with the intention of promoting urban cycling and improving cyclist safety. These facilities have been built and expanded but very little research has been done to investigate the safety impacts of cycle tracks, in particular at intersections, where cyclists interact with turning motor-vehicles. Some safety research has looked at injury data and most have reached the conclusion that cycle tracks have positive effects of cyclist safety. The objective of this work is to investigate the safety effects of cycle tracks at signalized intersections using a case-control study. For this purpose, a video-based method is proposed for analyzing the post-encroachment time as a surrogate measure of the severity of the interactions between cyclists and turning vehicles traveling in the same direction. Using the city of Montreal as the case study, a sample of intersections with and without cycle tracks on the right and left sides of the road were carefully selected accounting for intersection geometry and traffic volumes. More than 90 hours of video were collected from 23 intersections and processed to obtain cyclist and motor-vehicle trajectories and interactions. After cyclist and motor-vehicle interactions were defined, ordered logit models with random effects were developed to evaluate the safety effects of cycle tracks at intersections. Based on the extracted data from the recorded videos, it was found that intersection approaches with cycle tracks on the right are safer than intersection approaches with no cycle track. However, intersections with cycle tracks on the left compared to no cycle tracks seem to be significantly safer. Results also identify that the likelihood of a cyclist being involved in a dangerous interaction increases with increasing turning vehicle flow and decreases as the size of the cyclist group arriving at the intersection increases. The results highlight the important role of cycle tracks and the factors that increase or decrease cyclist safety. Results need however to be confirmed using longer periods of video data.

Keywords: Cycle Track, Cyclist Safety, Video Analysis, Surrogate Safety Measure, Random Effects Model

1. INTRODUCTION

In recent years, cities throughout North America have begun to follow Europe and Asia's lead and have started to build bicycle infrastructure. Until recently, some North American cities (e.g., Montreal, Portland, Ottawa, etc.) have been building and expanding their cycle track network but have not carried out many in-depth analyses to quantify their effects on cyclist safety, specifically at intersections where over 60 % of cyclist injuries occur (Strauss, Luis F Miranda-Moreno, et al. 2013). Now that cyclist numbers are on the rise, cyclist safety concerns at bicycle facilities have become an important issue. In the US and in Canada, some cities have implemented cycle tracks which are physically separated from vehicle traffic by concrete medians or bollards, as well as bicycle lanes delineated from vehicles by painted lines or simple sharrows (shared lane markings) along the roadway for vehicles and cyclists to share the same road. Facilities of these types can be found in cities like Montreal, Canada. Despite their increasing popularity, few studies have investigated whether or not cycle tracks are the appropriate solution and more specifically, how safe intersections with cycle tracks are for cyclists with respect to intersections without cycle tracks.

Previous studies have investigated the safety effects of cycle tracks using historical cyclist injury data also referred to as motor-vehicle-bicycle crash data (Thomas & DeRobertis 2013; Reynolds et al. 2009; Lusk et al. 2011; Teschke et al. 2012). Overall, the recent literature has identified some safety benefits for corridors with cycle tracks. However, these studies have not been able to fully answer the question of whether or not intersections with cycle tracks are safer than similar intersections without cycle tracks. Given the limitations of the crash data, these studies have not looked at cyclist injuries microscopically focusing on interactions between vehicles and cyclists as well as the geometry of the intersection. Only few studies have used surrogate safety measures or have relied on manual or semi-automated methods (Afghari et al. 2014; Sayed et al. 2013a). Also, past surrogate studies have involved one or very few locations (Afghari et al. 2014; Sayed et al. 2013a) and most have been carried out in Europe (Laureshyn et al. 2009; Phillips et al. 2011; Vogel 2003). Overall the previous literature has not investigated the specific question: what is the effect of cycle tracks on cyclist safety and more specifically what effect does building them on the right or left sides of the road have on safety.

In this work, we tackle the shortcomings in the current literature by developing an automated surrogate safety method, based on video data, to characterize cyclist-vehicle interactions. This method begins with video data extraction and ends with modeling cyclist-vehicle interactions. The proposed method is used to investigate the safety effects of cycle tracks at intersections focusing on interactions between turning vehicles and cyclists traveling in the same direction. For this purpose, a sample of intersections with cycle tracks (referred to as treated sites) and without cycle tracks (referred to as control sites) are carefully selected in the city of Montreal, Canada. This study is expected to provide additional insight into the risk of collision (in terms of probability) of bidirectional cycle tracks at intersections. Also, we expect that the proposed method is easily transferable and can be replicated in other cities.

A sample of 23 intersections were selected and categorized into 3 different groups. In total, more than 90 hours of video data was collected and processed to obtain the cyclist and vehicle trajectories. From the videos, post-encroachment time (PET) measures are computed automatically for each cyclist as a surrogate safety indicator. It is worth mentioning that among the advantages of surrogate analysis, is that interactions with different levels of severity can be observed, even in the short-term (hours), as opposed to the traditional approach (with crash data), where no or very few accidents are observed over a long period of time (months and years). Another advantage of the video-based surrogate safety method is its ability to extract information about the factors influencing interactions, such as bicycle and motor-vehicle flows at different levels of aggregation (as is desired) (Zangenehpour, Romancyshyn, et al. 2015).

This paper is divided into several sections. First a review of the literature on cyclist safety at cycle tracks, surrogate safety measures as well as automated methods is provided. This is followed by a detailed description of the proposed automated video based methodology. The paper then presents and discusses the modelling results and finally provides the conclusions that are drawn from this study and future work.

2. LITERATURE REVIEW

Several studies have been published in recent years on cyclist safety in urban environments. In particular, some of these studies have investigated cyclist injury risk and its associated factors. Given the rising popularity of cycle tracks, few studies have investigated cycle tracks to identify and quantify their safety effectiveness. The majority of recent studies have concluded that corridors with cycle tracks are either safer or at least not more dangerous than corridors without cycle tracks. We can refer to the literature review of Thomas and deRobertis (Thomas & DeRobertis 2013) which examined the literature on cycle tracks from different countries mostly in Northern Europe and one study in Canada. Overall, it was found that one-way cycle tracks are safer than bidirectional cycle tracks and that in general, cycle tracks reduce collisions and injuries when effective intersection treatments are also implemented. Another review of the literature by Reynolds et al. (Reynolds et al. 2009), revealed that bicycle-specific facilities, not shared roads with vehicles or shared off-road paths with pedestrians, reduce both the risk of accidents and injuries. Also, of the 23 studies reviewed in (Reynolds et al. 2009), eight examined safety at intersections which were for the most part roundabouts.

To investigate the effectiveness of safety treatments, road safety studies can be divided into: i) cross-sectional studies in which data from a sample of locations or intersections with different geometry and built environment characteristics are used (Strauss, Luis F Miranda-Moreno, et al. 2013; Miranda-Moreno et al. 2011; Wang & Nihan 2004), ii) before-after studies, in which data from before and after treatment implementation is available from a sample of treated and non-treated locations (Dill et al. 2012; Gårder et al. 1998; S. U. Jensen 2008; Zangenehpour 2013; S. Jensen 2008), and iii) case-control studies in which data from a sample of intersections contains two subsets: a subsample of intersections in which the treatment exists and a subsample of intersections with very similar characteristics (same traffic intensity, geometry) but without treatment (Lusk et al. 2011; Chen et al. 2012).

A case-control study carried out in Montreal (Lusk et al. 2011), compared cyclist injury rates on six bidirectional cycle tracks and compared them to that on reference streets. Bicycle flows were found to be 2.5 times greater on tracks than on the reference streets and the relative risk of injury on tracks was found to be 0.72 compared to the reference streets, supporting the safety effects of cycle tracks. A study looking at bicycle infrastructure in Toronto and Vancouver found that cycle tracks have the lowest injury risk compared to other infrastructure types and with one ninth of the risk of major streets with parked cars and no bicycle infrastructure (Teschke et al. 2012). Overall quiet streets and bicycle facilities on busy streets provide safest passage for cyclists. An older before-after study in Denmark found that cycle tracks increased bicycle flows by 20 % while decreased vehicle mileage by 10 % (S. Jensen 2008). However, overall, injuries were found to increase with the implementation of cycle tracks. While injuries were reduced along links, the increase in injuries at intersections was greater than this decrease. The author identified that cycle tracks which end at the stop line of the intersection are dangerous. A decade prior, Gårder et al. (Gårder et al. 1994) came to a similar conclusion in Sweden, that physically separated tracks should be cut some short distance before the intersection which would not only improve visibility but also cause cyclists to feel less safe influencing them to pay greater attention at intersections.

In this emerging literature, it is worth highlighting that most empirical evidence about the effectiveness of cycle tracks are based on historical crash data, referred to as the traditional safety approach. Studies using surrogate safety measures are beginning to gain popularity in the bicycle literature (Sayed et al. 2013a; Afghari et al. 2014). However, surrogate safety analysis looking specifically at the effects of cycle tracks are rare in the current literature. In addition, most surrogate safety studies consider only one or a small sample of intersections.

Automated methods for surrogate safety analysis have begun to emerge in the literature (Sayed et al. 2013a; Kassim et al. 2014; Sakshaug et al. 2010). A recent study in Vancouver presented the use of an automated method to obtain Time-To-Collision (TTC) to identify the severity of cyclist interactions at one busy intersection (Sayed et al. 2013a). Another recent study in Ottawa evaluated cyclist-vehicle interactions at signalized intersections based on post-encroachment time (PET) (Kassim et al. 2014). These studies however have not looked at the effectiveness of cycle tracks.

3. METHODOLOGY

This section describes the methodology which consists of the following steps: i) site selection and video data collection, ii) data processing and iii) statistical analysis. Additional details for each step are provided as follows.

3.1. Site Selection and Video Collection

To investigate the safety effects of cycle tracks, more than 90 hours of video were recorded from intersections both with and without cycle tracks, all of them in Montreal. A sample of sites with cycle tracks on the right side of the road, on the left side of the road and control sites without cycle tracks (or any other bicycle facilities) were carefully selected. It is worth mentioning that all the studied cycle tracks in this paper are bidirectional. External sources of bicycle and vehicle traffic flow data helped us identify sites with and without cycle tracks with high levels of bicycle flow providing a large number of cyclists to study. All intersections in this study are four-legged and signalized where at least one approach is defined as an arterial or a collector. Due to summer road closures and construction, in some cases, alternate sites had to be selected. For each cycle track on the right, video was collected the exact same day and time at a control site. The control sites were selected on parallel streets but without any bicycle infrastructure. Where possible, parallel streets were selected since these streets provide an alternative route for cyclists who do not wish to ride along the street with a cycle track. Also, the control sites were selected to have similar vehicle traffic conditions. No control sites were selected for cycle tracks on the left since streets without cycle tracks on the left would have cyclists riding on the right and therefore this type of interaction does not exist anywhere but where the cycle track is on the left.

For the video data collection, GoPro Hero 3+ Black Edition cameras were used in HD resolution at 15 frames per second. These cameras were mounted on tall poles which are then installed next to an existing pole at the intersection to support and provide stability for the pole to prevent the camera view from changing during the video recording. Where possible, these poles were set up on the approach opposite and facing the interaction area. In some cases, alternate poles and locations were necessary since there was no pole at some intersections or the location of the traffic signals prevented the camera from being mounted in the ideal location. Using available bicycle flow data from automatic counters, we were able to identify the peak cycling hours. For this data collection, evening peak was selected as the study period in order to ensure a sufficient number of cyclists to study. Videos were collected on weekdays during the evening peak period from 15:00 to 19:00 for two to four hours with few exceptions. The camera angle differed for each site since the angle was selected to provide the best view of the interaction area and the cyclists and vehicles entering and leaving the interaction area to accurately obtain their trajectories. Depending on the width of the road, the location of an appropriate pole as well as other obstacles, the camera setup differed between sites.

3.2. Data Processing

Data processing includes four steps: detecting and tracking moving road users in the video, classifying the road users into their road user types (pedestrian, cyclist or vehicle), selecting the road users involved in the interactions under study, and computing the surrogate safety measures for each cyclist-vehicle interaction (Zangenehpour, Miranda-Moreno, et al. 2015). Further details are provided as follows.

3.2.1. Tracking Road users in Video

An existing feature-based tracking tool from an open-source project called Traffic Intelligence (Saunier n.d.) is used for detecting and tracking the road users in the video. The proposed approach uses the output of the moving object tracker (Saunier & Sayed 2006).

The tracker output is a set of trajectories (sequence of road user’s position in each frame) of each moving road user in the video. The parameters of this algorithm are tuned through trial and error, leading to a trade-off between over-segmentation (one road user tracked as many) and over-grouping (many road users tracked as one). Readers are referred to (Saunier & Sayed 2006) for more details.

3.2.2. Road User Classification

At intersections with different road user types, road user classification is needed, especially when the focus of the study is on the interactions between two different road user types. In this paper, a modification of the previously developed method for road user classification in video (Zangenehpour et al. 2014) has been used. Classification is achieved based on the road user's appearance in each frame combined with its aggregated speed and speed frequency (or gait parameters). The overall accuracy of this classification method at intersections with high volumes and mixed road user traffic is around 93 % (a 5 % point improvement from the original classification method presented in *(26)*). The classifier is capable of classifying road users into three main road user types: pedestrian, cyclist, and motor-vehicle. For more details regarding the original classification method, readers are referred to (Zangenehpour et al. 2014).

3.2.3. Selecting Trajectories

Only the interactions between cyclists and turning vehicles traveling in the same direction, are of interest in this study. Interacting cyclists and turning vehicles are selected by defining origin and destination areas in the field of view. A trajectory will be selected as a desired cyclist (or vehicle) if:

1- the road user is classified as a cyclist (or vehicle)
2- the road user passes through the origin area defined for cyclists, B1 (or vehicles, V1) (Figure 1)
3- after the road user passes through the origin area, it passes through the destination area defined for cyclists, B2 (or vehicles, V2) (Figure 1)

One sample of a density map derived from the trajectories (both cyclists and turning vehicles) extracted and filtered by this algorithm is shown in Figure 1. This density map is useful to see the most used locations of the map by the cyclists and turning vehicles.

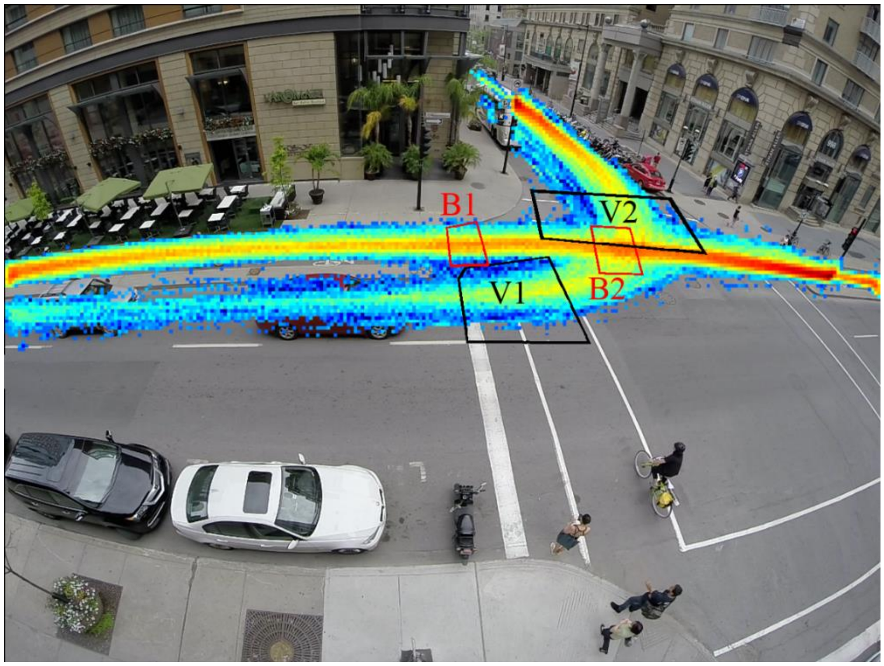

Figure 1. Position density map of the studied cyclists and turning vehicles in a sample video[1]

3.2.4. Surrogate Safety Indicator

The surrogate measure of safety used in this study to evaluate the severity of each interaction is PET. This measure is the time between the departure of the encroaching cyclist from the potential collision point (at the intersection of the two trajectories) and the arrival of the first vehicle at the potential collision point at the intersection, or vice versa (Gettman & Head 2003; Laureshyn et al. 2010). PET is preferred over TTC in this study since all interactions of interest involve the road users' paths crossing one another, so that PET can always be computed. TTC is a widely used surrogate safety measure that depends on the choice of a motion prediction method. The most common motion prediction is constant velocity, which is inappropriate in many practical cases, in particular if the interactions under study involve turning movements as it does in this study. Several methods exist to alleviate this issue (Mohamed & Saunier 2013), but PET was found to be sufficient for this study.

Once the desired trajectories are extracted (the ones for cyclists and turning vehicles), PET can be calculated using the time difference between the instants the two road users (one cyclist and one turning vehicle) pass through the point where their trajectories intersect. Since the position of each road user is identified by its center point, PET is computed based on the time difference between the instants at which the road users are within a threshold distance of the trajectory crossing points (selected as one meter). PET is selected for each cyclist as the minimum PET

[1] The most and least used map locations are respectively red and blue, density map colours range from blue to red, passing through cyan, yellow, and orange. B1 and V1 are the origin areas while B2 and V2 are the destination areas for cyclists and vehicles, respectively.

value for each cyclist with each turning vehicle which turned either before or after the cyclist crossed the intersection.

3.3. Statistical Modeling

For the analysis, two approaches are used: raw-risk estimates and statistical models. For the raw-risk estimates, interaction rates and dangerous interaction rates at intersections with cycle tracks and intersections without cycle tracks are compared. These rates are defined as follows:

$$IR_t = \frac{(NPET_t) \, * \, 10^6}{(Cyclists\ per\ hour) \, * \, (Turning - Vehicles\ per\ hour)} \qquad (1)$$

Where in (1):

- IR_t is the interaction rate for a predefined PET threshold value denoted by *t*.
- $NPET_t$ is the number of cyclists with at least one interaction with PET below *t*, per hour. It is possible that the same cyclist has interactions with more than one vehicle but in this work we just consider the most dangerous interaction (with the lowest PET).
- *t* is a predefined PET threshold value, 1.5 seconds for dangerous interactions and 5 seconds for interactions.

The definition of *t* has been arbitrary selected and is in agreement with the thresholds used in the literature (Sayed et al. 2013b). It is worth mentioning that other *t* values have been tested and the results were found to be robust.

In the second analysis, a statistical modeling approach is used. For this purpose, the PET value of each individual cyclist arriving to the intersection with the turning vehicle that turns closest in time to the cyclist (the one that provides the minimum PET for the cyclist) is used as the dependent variable. Only the cyclists riding parallel to the motor-vehicles, in the same direction (prior to turning), are the focus of this study, as shown in Figure 2. In order to provide meaningful results, PET values (for each cyclist) are discretized into four categories, defined as:

1. PET ≤ 1.5 seconds, considered as a very dangerous interaction,
2. 1.5 seconds < PET ≤ 3 seconds, considered as a dangerous interaction,
3. 3 seconds < PET ≤ 5 seconds, considered as a mild interaction, and
4. PET > 5 seconds, considered as no interaction.

Note that as a sensitivity analysis, other thresholds for defining the categories have been tested; however small changes in the threshold values did not significantly change the results. Once PET is discretized, random effects ordered logit models are applied to control for the effects of other variables such as traffic conditions and road geometry as well as the random effect and unobserved variables of each intersection. The random effect ordered logit model is one of the most commonly used statistical models for crash severity analysis. For more details about the random effect ordered logit model, please refer to (Crouchley 1995). In this model, $y_{ij} = \beta x_{ij} + \varepsilon_{ij} + \delta_j$, where y_{ij} is the PET latent variable for observation *i* at site *j*, x_{ij} is the vector of attributes for interaction *i* at site *j*, β is the vector of unknown parameters, ε_{ij} is the individual error term for each observation and δ_j is the random effect at the intersection level considering that measurements obtained from the same intersections are nested. The dependant variable, y_{ij}, is bound by unknown cut-offs, which define the alternatives.

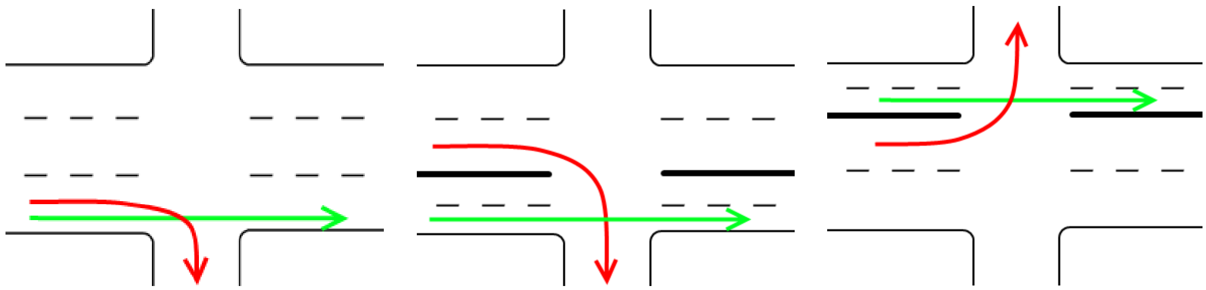

Figure 2. Studied interactions for three different types of intersections: (a) cyclists and right-turning vehicles at intersections without cycle track, (b) cyclists and right-turning vehicles at intersections with cycle track on the right, and (c) cyclists and left-turning vehicles at intersections with cycle track on the left. Red and green arrows show turning vehicles and cyclists respectively

Several variables were generated and tested as potential independent variables associated with the severity of interactions, including:

- Cycle track on the right side of the road (dummy variable).
- Cycle track on the left side of the road (dummy variable).
- Number of lanes on the approach where the vehicles is turning from, parallel to where cyclists are riding.
- Number of lanes on the approach where vehicles turn into.
- Presence of bus stops at the intersection (dummy variable).
- One way street (dummy variable).
- Turning vehicle and cyclist flows per hour.

Disaggregate exposure measures are also considered in the proposed modeling approach, such as the number of cyclists and turning vehicles arriving before and after the arrival of each individual cyclist. Considering cyclist i (C_i) arrives at time t_i, these variables are defined individually for cyclist i as:

- Bicycle flow before C_i = number of cyclists arriving between t_i - t_b and t_i.
- Bicycle flow before and after C_i = number of cyclists arriving during $t_i \pm t_{ba}$.
- Vehicle flow before C_i = number of turning vehicles between t_i - t_b and t_i.
- Vehicle flow before and after C_i = number of turning vehicles arriving during $t_i \pm t_{ba}$.

Where t_b represents a predefined time interval before the arrival of cyclist i of 10, 30, or 60 seconds and t_{ba} represents a predefined time interval before and after the arrival of cyclist i of 5, 15, or 30 seconds. Different time intervals were selected and tested to determine which has the greatest effect on cyclist safety with respect to turning vehicles at intersections. The proposed method for counting cyclists in different movements has been shown in (Zangenehpour, Romancyshyn, et al. 2015) to provide acceptable counting accuracy.

Using the variables defined previously, different models were proposed to investigate the safety effect of cycle tracks on interactions between cyclists and turning vehicles. Three models are developed to compare:

1- Intersections with a cycle track on the right side to intersections without a cycle track.
2- Intersections with a cycle track on the left side to intersections without a cycle track.
3- Intersections with a cycle track on the right side to intersections with a cycle track on the left side.

3.4. Validation of the Accuracy of PET Measures

The use of automated video analysis for detecting conflicts and extracting surrogate measures of safety is not new. The accuracy of the video analysis algorithms integrated in "Traffic Intelligence" has been validated in previous studies; for instance one can refer to (St-Aubin et al. 2015) in regards to its tracking accuracy, (Zangenehpour, Romancyshyn, et al. 2015) in regards to its accuracy in counting cyclists in various conditions, and (Anderson-Trocmé et al. 2015) in regards to its accuracy in measuring speed.

In order to show the accuracy of the automated method to estimate the PET category of each interaction, 50 samples (based on the automated method) from each category were randomly selected and reviewed manually by the authors (Table 1). The overall classification acuracy of the automated method is determined to be 88 %.

Table 1. Confusion matrix showing the accuracy of the method to estimate PET categories

		Manual					
		PET ≤ 1.5	1.5 < PET ≤ 3	3 < PET ≤ 5	PET > 5	Total	Precision
Automated	PET ≤ 1.5	42	6	1	1	50	84 %
	1.5 < PET ≤ 3	1	44	3	2	50	88 %
	3 < PET ≤ 5	0	3	46	1	50	92 %
	PET > 5	0	0	6	44	50	88 %
	Total	43	53	56	48		
	Recall	98 %	83 %	82 %	92 %		88%

4. DATA AND RESULTS

Video and geometry data were obtained for a sample of 23 intersections. More specifically, a total of over 90 hours of video data was collected, from which around 31 hours of video were collected from intersections with no cycle track (8 sites), around 37 hours for intersections with cycle track on the right side of the road (8 sites) and more than 22 hours for intersections with cycle track on the left side of the road (7 sites). Figure 3 provides the locations of these intersections.

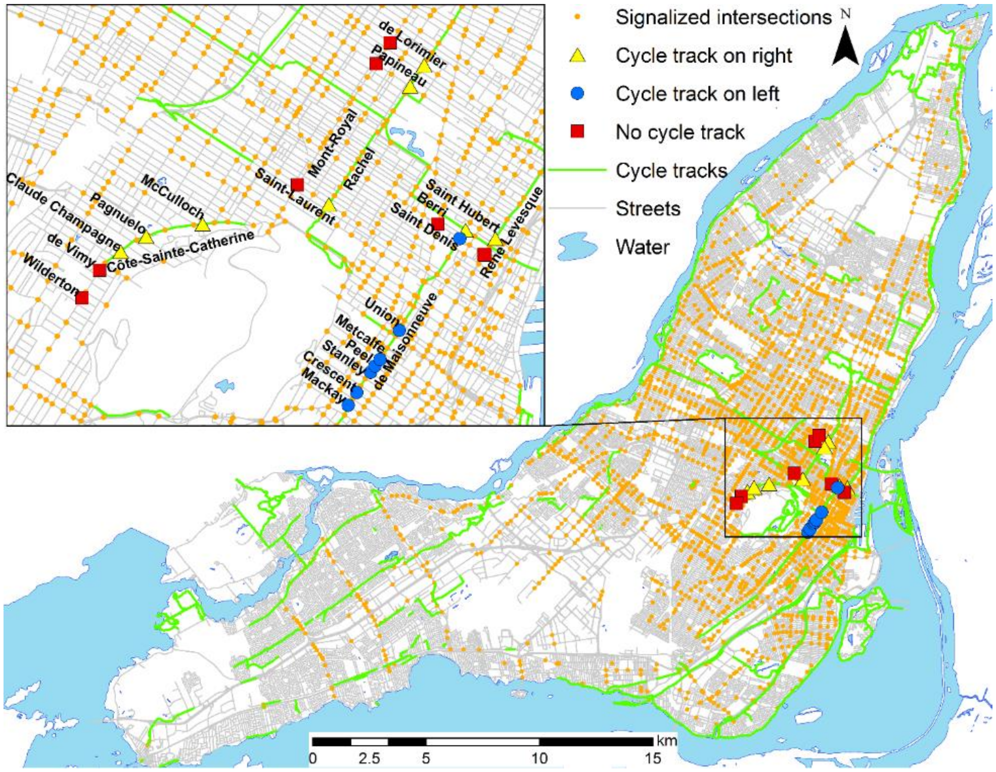

Figure 3. Location of sites selected for recording video in Montreal

A summary of the video analysis for the recorded video is shown in Table 2 which shows that:

- Bicycle flow is higher at intersections with a cycle track, an average of 18 cyclists per hour for intersections without a cycle track, 63 for intersections with a cycle track on the right side and 191 for intersections with a cycle track on the left side (all the cycle tracks on the left side are on Maisonneuve Boulevard which is one of the busiest cycle tracks in Montreal). This shows that either cyclists prefer to use roads with cycle tracks, or cycle tracks were implemented on roads that have more bicycle flow.
- Looking at the averages at the bottom of the table, the average cyclist speeds are found to be similar across site subgroups. Speed is only slightly higher at intersections with cycle tracks where cyclists feel safe and are provided with their own space to bike at their desired speed. Additionally, as expected, average cyclist speed is greater for cyclists riding in the downhill direction at intersections (like on Cote Sainte Catherine).
- The number of interactions and dangerous interactions per hour are on average greater at intersections with cycle tracks. However, accounting for bicycle and turning vehicle flows, the rate of dangerous interactions is lower for intersections with cycle tracks, as illustrated in Figure 4.
- Figure 5 shows the position density maps for cyclists and turning vehicles for three different intersection types. These density maps show the acceptable accuracy of detecting, tracking, and classifying road users in the videos. In addition, it shows the average distance between cyclists and turning vehicles at intersections, which can also be related to safety.

Table 2. Summary of the processed videos, counts and speeds for cyclists and vehicles

	Intersection	Hours of video	Number of Bicycles	Number of Vehicles	Cyclist Average Speed (km/h)	Vehicle Average Speed (km/h)	PET ≤ 5	PET ≤ 1.5	Cyclists per Hour	Vehicles per Hour	PET ≤ 5 per Hour	PET ≤ 1.5 per Hour	Interaction Rate*	Dangerous Interaction Rate*
No Cycle Track	Cote Sainte Catherine / Vimy	6.54	56	323	14.3	18.9	6	2	8.6	49.4	0.9	0.3	2169.4	723.1
	Cote Sainte Catherine / Wilderton	8.32	90	843	12.6	9.8	13	2	10.8	101.3	1.6	0.2	1425.6	219.3
	Mont Royal / Lorimier	2.88	106	66	10.9	12.6	4	2	36.8	22.9	1.4	0.7	1646.7	823.3
	Mont Royal / Papineau	1.74	48	50	13.8	10.4	5	2	27.6	28.7	2.9	1.1	3625.0	1450.0
	Mont Royal / Saint Laurent	2.71	53	150	10.4	8.2	6	3	19.6	55.4	2.2	1.1	2045.3	1022.6
	Rene Levesque / Saint Denis	2.8	116	237	10.5	9.3	19	2	41.4	84.6	6.8	0.7	1935.1	203.7
	Saint Denis / Ontario	2.95	43	62	10.1	12.3	2	0	14.6	21.0	0.7	0.0	2213.1	0.0
	Saint Denis / Rene Levesque	2.98	46	328	12.2	14.1	9	3	15.4	110.1	3.0	1.0	1777.6	592.5
Cycle Track on Right	Berri / Maisonneuve	2.89	188	90	8.7	8.4	11	0	65.1	31.1	3.8	0.0	1878.8	0.0
	Cote Sainte Catherine / Claude Champagne	8.28	436	153	18.1	17.8	27	1	52.7	18.5	3.3	0.1	3351.3	124.1
	Cote Sainte Catherine / Mcculloch	7.14	236	125	18.8	18.9	7	0	33.1	17.5	1.0	0.0	1694.2	0.0
	Cote Sainte Catherine / Pagnuelo	8.08	383	340	10.0	13.8	29	1	47.4	42.1	3.6	0.1	1799.4	62.0
	Rachel / Lorimier	2.5	142	63	11.8	11.0	12	0	56.8	25.2	4.8	0.0	3353.5	0.0
	Rachel / Papineau	2.1	226	390	11.7	12.3	16	9	107.6	185.7	7.6	4.3	381.2	214.4
	Rachel / Saint Laurent	2.98	106	350	10.7	9.8	23	6	35.6	117.4	7.7	2.0	1847.4	481.9
	Rene Levesque / Saint Hubert	2.98	605	175	15.7	13.1	76	4	203.0	58.7	25.5	1.3	2139.1	112.6
Cycle Track on Left	Maisonneuve / Crescent	3.5	787	558	14.2	13.7	245	17	224.9	159.4	70.0	4.9	1952.7	135.5
	Maisonneuve / Makay	3.33	476	291	12.5	12.2	82	9	142.9	87.4	24.6	2.7	1971.3	216.4
	Maisonneuve / Metcalfe	3.28	820	358	13.3	12.1	163	15	250.0	109.1	49.7	4.6	1821.2	167.6
	Maisonneuve / Peel	3.48	500	222	13.2	10.4	68	8	143.7	63.8	19.5	2.3	2131.9	250.8
	Maisonneuve / Saint Denis	3.22	398	219	14.2	12.3	73	4	123.6	68.0	22.7	1.2	2696.8	147.8
	Maisonneuve / Stanley	3.32	956	247	12.6	12.4	135	12	288.0	74.4	40.7	3.6	1898.1	168.7
	Maisonneuve / Union	2.09	308	147	14.3	15.5	30	0	147.4	70.3	14.4	0.0	1384.8	0.0
Total	No Cycle Track	30.92	558	2059	11.7	11.9	64	16	18.0	66.6	2.1	0.5	1722.4	430.6
	Cycle Track on Right	36.95	2322	1686	14.0	12.9	201	21	62.8	45.6	5.4	0.6	1897.1	198.2
	Cycle Track on Left	22.22	4245	2042	13.4	12.7	796	65	191.0	91.9	35.8	2.9	2040.4	166.6

* Computed based on equation (1)

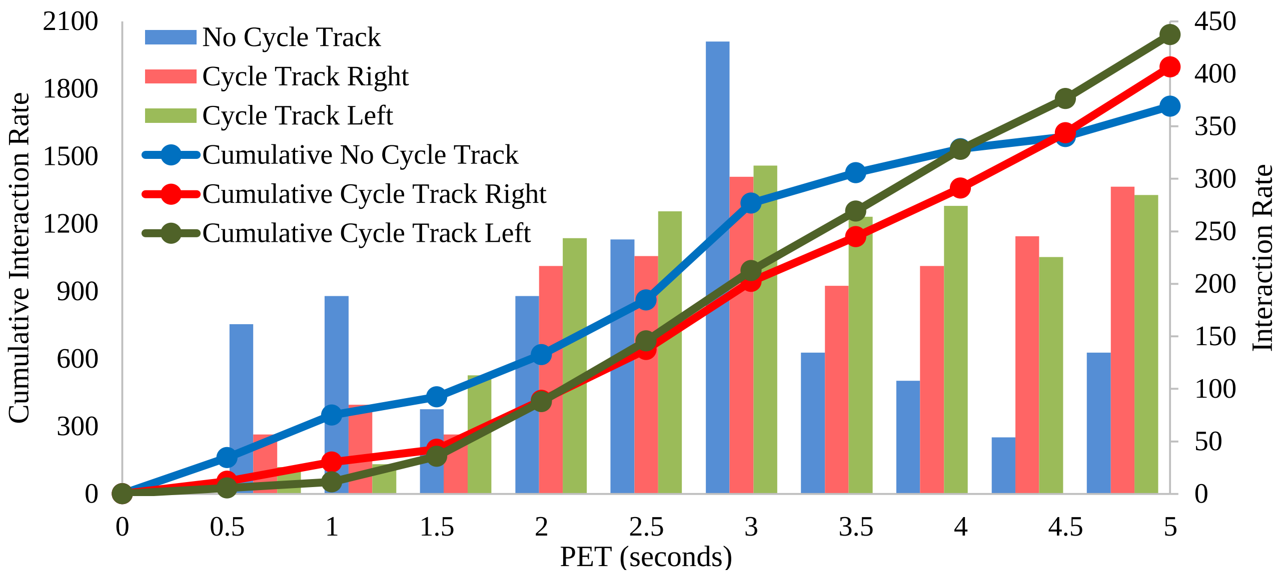

Figure 4. Interaction rate and cumulative interaction rate per PET interval

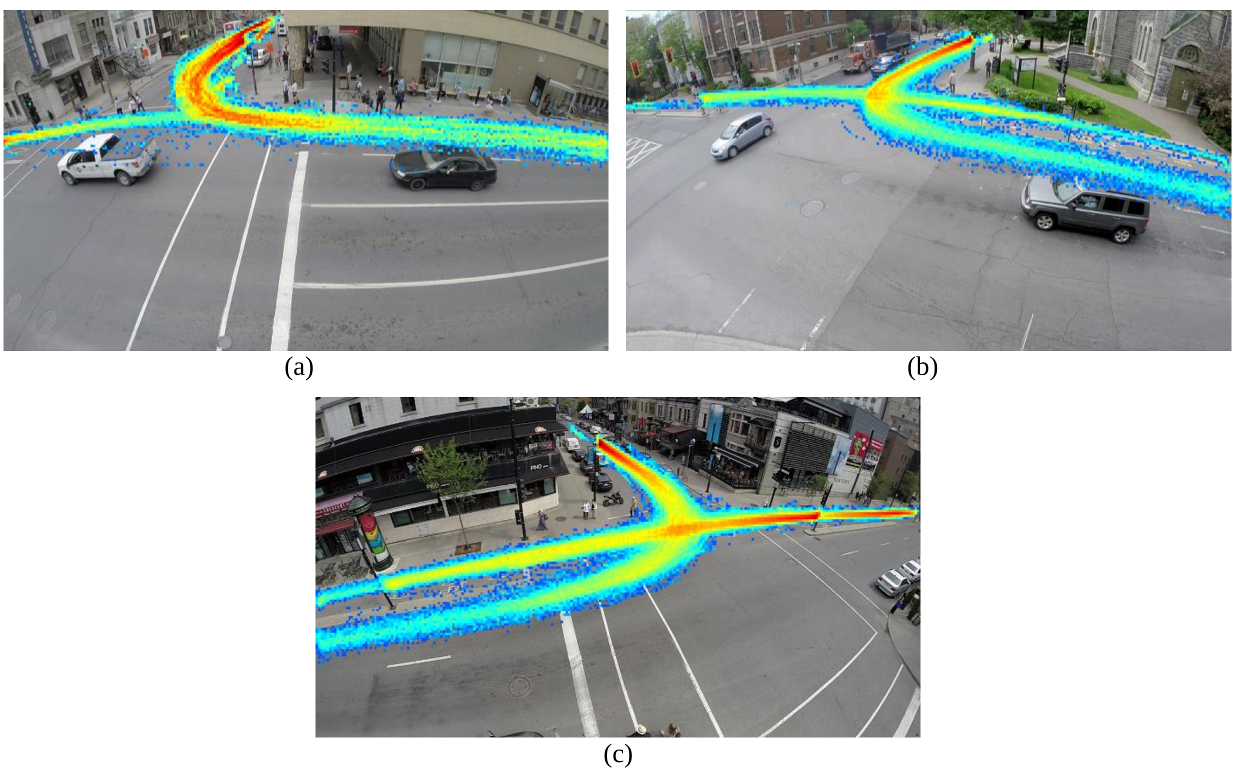

Figure 5. Position density map of cyclists and turning vehicles for three sample intersections, intersection with no cycle track (a), intersection with a cycle track on the right side of the road (b), and intersection with a cycle track on the left side of the road (c).

The final random effects ordered logit modelling results for PET values are shown in Table 3. Note that different combinations of variables were used to find the best model, and only variables significant to the 95 % confidence level, which do not have high correlation with any other variable, are introduced and presented in the final models.

Table 3. Model results for interactions between cyclists and turning vehicles

	Model I. Cycle track on the right vs. no cycle track			**Model II. Cycle track on the left vs. no cycle track**			**Model III. Cycle track on the right vs. cycle track on the left**		
	Coef.	Std. Err.	Sig.	Coef.	Std. Err.	Sig.	Coef.	Std. Err.	Sig.
Cycle Track on Right	0.395	0.181	0.03	-	-	-	-	-	-
Cycle Track on Left	-	-	-	Not Significant			-0.513	0.131	0.00
Bicycle Flow for 5s before to 5s after	Not Significant			0.088	0.038	0.02	0.066	0.034	0.05
Turning vehicle Flow for 5s before to 5s after	-2.771	0.132	0.00	-3.265	0.090	0.00	-3.131	0.080	0.00
Number of Lane on the Main Road	-0.151	0.078	0.05	Not Significant			Not Significant		
Number of Lane on the Turning Road	Not Significant			0.324	0.146	0.03	0.457	0.178	0.01
Cut-off 1	-6.599	0.353	0.00	-7.372	0.301	0.00	-7.621	0.323	0.00
Cut-off 2	-4.233	0.273	0.00	-3.807	0.223	0.00	-4.125	0.265	0.00
Cut-off 3	-3.150	0.256	0.00	-2.102	0.211	0.00	-2.479	0.258	0.00
Number of Observations	2880			4803			6567		
Log likelihood	-804			-1876			-2330		

The main goal of this regression analysis is to complement and confirm the observed safety effects of cycle tracks based on interaction rates between cyclists and turning vehicles. The advantage of regression analysis is that one is able to simultaneously control for geometry and traffic conditions while the raw-risk estimates (interaction rates) assume that the number of interactions is a linear function of the number of cyclists and vehicles involved. Not surprisingly, the results of the regression analysis are in the same direction and show that intersections with cycle tracks on the right are safer for cyclists compared to intersections without cycle tracks (Model I). Based on the predictions made by this model, and with the assumption that all the relevant variables are included in the models, if cycle tracks (on the right side of the road) are built at all the intersections which currently do not have any cycle track, while keeping all else constant, the expected number of dangerous interactions (interactions with PET $\leq$ 3 seconds) does not change but the number of interactions (interactions with PET $\leq$ 5 seconds) is expected to decrease by around 40 % (from 1.07 to 0.65 interactions per hour). However, intersections with cycle tracks on the left side (all on Maisonneuve Boulevard) are not significantly safer than intersections without cycle tracks (Model II). Another finding is that cycle tracks on the right are safer than cycle tracks on the left side (Model III). This may be due to the lateral distance between cyclists and vehicles. At intersections with cycle tracks on the right (Figure 6a), the lateral distance between a cyclist and a vehicle in the same direction is greater than at intersections with cycle tracks on the left (Figure 6b). This means that cyclists and drivers have a greater chance of seeing one another and avoiding dangerous interactions. If cycle tracks are moved from the left side to the right side of the intersection, while keeping all else constant, based on the predictions made by this model, the expected number of dangerous interactions (interactions with PET ≤ 3 seconds) does not change but the number of interactions (interactions with PET ≤ 5 seconds) is expected to decrease by around 25 % (from 32.5 to 24.7 interactions per hour). These elasticities were computed based on each individual cyclist and with the assumptions of building cycle tracks at the intersections currently without cycle tracks in Model I, and changing the position of cycle tracks at the intersections with cycle tracks on the left to the right side in Model III. Note that these elasticities were computed based on the assumption that all the relevant variables have been included in the models. It is possible, however, that some relevant variables cannot be measured or quantified and therefore included in the models. Such variables include cyclists' and drivers' gender, age, and experience as well as their personality and their level of aggression.

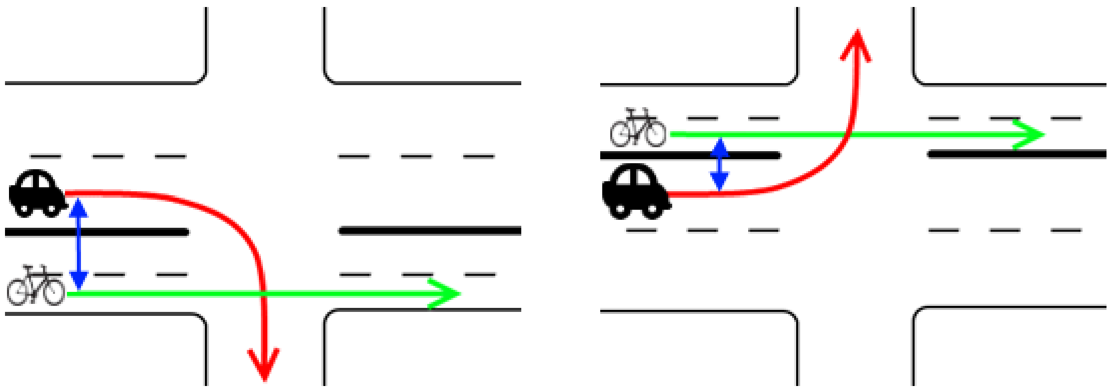

Figure 6. Interaction between cyclists and turning vehicles (the red arrows show a trajectory sample of turning vehicles, the green arrows show a trajectory sample of cyclists and the blue arrow shows the lateral distance between cyclists and vehicles), for intersections with a cycle track on the right side (a), and for intersections with a cycle track on the left side (b).

Results also show that the number of turning vehicles is the main factor associated with intersections being dangerous for each individual cyclist. Higher turning vehicle flow at the time that a cyclist is crossing the intersection provides smaller gaps for the cyclist crossing the intersection and increases the chance of a cyclist being involved in a more dangerous interaction with one of the turning vehicles.

Another variable that makes an intersection dangerous for cyclists is the number of lanes on the main road (the road that vehicles are turning from), meaning that the more lanes on the main road, the more dangerous it is for cyclists on that road (just for Model I).

The bicycle flow before and after C_i, defined as the number of cyclists arriving at the intersection between $t_i – 5$ and $t_i + 5$, reduces the risk for each individual cyclist. This means that as the arrival rate of cyclists increases, the chance of being seen by drivers also increases. This variable represents the safety effect of group arrivals and can also be seen as the "safety in numbers" effect (Jacobsen 2003). Note that this variable was not significant for comparing intersections with cycle tracks on the right to intersections with no cycle track (Model I).

The higher the number of lanes on the road that vehicles turn into is another variable that can make intersections safer for cyclists. More lanes on the road, on to which vehicles turn, means that turning vehicles have more manoeuvering options for their turning radius to avoid interactions with cyclists. This variable was not significant for comparing intersections with cycle tracks on the right to intersections with no cycle track (Model I).

It is worth mentioning that a sensitivity analysis was carried out to ensure that the results are independent of the threshold values chosen to discretize the PET values. Several different thresholds were tested and all the parameter estimates were found to be consistent.

5. VALIDATION OF SURROGATE SAFETY MEASURES

To validate the relationship of the surrogate safety measure used in this study with actual safety, we compared the rankings of the 23 studied intersections based on historical accident data to the rankings based on the surrogate safety measure. The historical accident data came from ambulance services in Montreal over a six year period from 2007 to 2012. At locations with cycle tracks, only accidents that occurred after the track was built were considered. Also, the accident data used is for the entire intersection, considering total vehicle and bicycle flows, and not specifically for the cyclists traveling straight and turning vehicles. This analysis therefore assumes that the ratio of total accidents to total flows can be used as a proxy for the ratio of accidents between cyclists traveling straight and vehicles turning to their respective flows. In the accident database, accidents were considered as having occurred at an intersection if they were within fifteen meters of the centre point of the intersection. Although ambulance data may be biased towards more severe injuries, in Montreal, this source of data identified more cyclist injuries than police reports (Strauss, Luis F. Miranda-Moreno, et al. 2013).

For ranking the intersections based on crash data, equation (2), which has been widely accepted and used in the literature (Strauss, Luis F. Miranda-Moreno, et al. 2013), was applied:

$$Accident\ Rate = \frac{Accident\ per\ year * 10^6}{AADB * 365} \quad (2)$$

Where, AADB is the average annual daily bicycle volume achieved by combining smartphone GPS and manual count data in Montreal (Strauss et al. 2015). Other exposure measures were used in the rest of this paper to correlate the interaction and accident rate.

For the ranking based on interactions, equation (1) was used with *t* equal to 1.5 seconds in order to identify only very dangerous interactions. The summary of accident, flow and interaction data for the 23 studied intersections is presented in Table 4.

Table 4. Summary of accident, flow and surrogate measure of safety

Intersection	Observed accidents	Years of data	Number of accidents per year	AADB	Accident rate*	Dangerous interaction rate**	Accident rank	Interaction rank
Mont Royal / Papineau	13	6	2.17	898	6.608	1450	1.0	1.0
Cote Sainte Catherine / Vimy	1	6	0.17	319	1.433	723	2.0	4.0
Cote Sainte Catherine / Claude Champagne	5	3	1.67	4437	1.030	124	3.0	3.0
Mont Royal / Lorimier	3	6	0.50	1768	0.775	823	4.0	16.0
Mont Royal / Saint Laurent	2	6	0.33	2180	0.419	1023	5.0	2.0
Maisonneuve / Crescent	7	5	1.40	9674	0.397	136	6.0	5.0
Saint Denis / Rene Levesque	1	6	0.17	1330	0.342	593	7.5	11.0
Rene Levesque / Saint Denis	1	6	0.17	1330	0.342	204	7.5	15.0
Maisonneuve / Mackay	5	5	1.00	8277	0.332	216	9.0	9.0
Cote Sainte Catherine / Pagnuelo	2	3	0.67	5590	0.326	62	10.0	7.0
Maisonneuve / Peel	5	5	1.00	9662	0.285	251	11.0	14.0
Maisonneuve / Saint Denis	6	5	1.20	11803	0.279	148	12.0	6.0
Cote Sainte Catherine / Mcculloch	1	3	0.33	4023	0.227	0	13.0	12.0
Maisonneuve / Stanley	4	5	0.80	11142	0.197	169	14.0	18.0
Rachel / Saint Laurent	5	6	0.83	13331	0.173	482	15.0	21.0
Maisonneuve / Union	7	5	1.40	32997	0.115	0	16.0	21.0
Rachel / Papineau	7	3	2.33	67336	0.096	214	17.0	10.0
Rachel / Lorimier	7	6	1.17	68256	0.047	0	18.0	21.0
Saint Denis / Ontario	2	6	0.33	24554	0.038	0	19.0	21.0
Rene Levesque / Saint Hubert	1	6	0.17	20165	0.022	113	20.0	17.0
Berri / Maisonneuve	3	5	0.60	83130	0.019	0	21.0	21.0
Cote Sainte Catherine / Wilderton	0	6	0.00	318	0.000	219	22.5	8.0
Maisonneuve / Metcalfe	0	5	0.00	11475	0.000	168	22.5	13.0

* accidents per million cyclists

** dangerous interactions per million potential interactions

Figure 7 visually shows the relationship between the ranking based on the accident data and the ranking based on the dangerous interactions observed in this study.

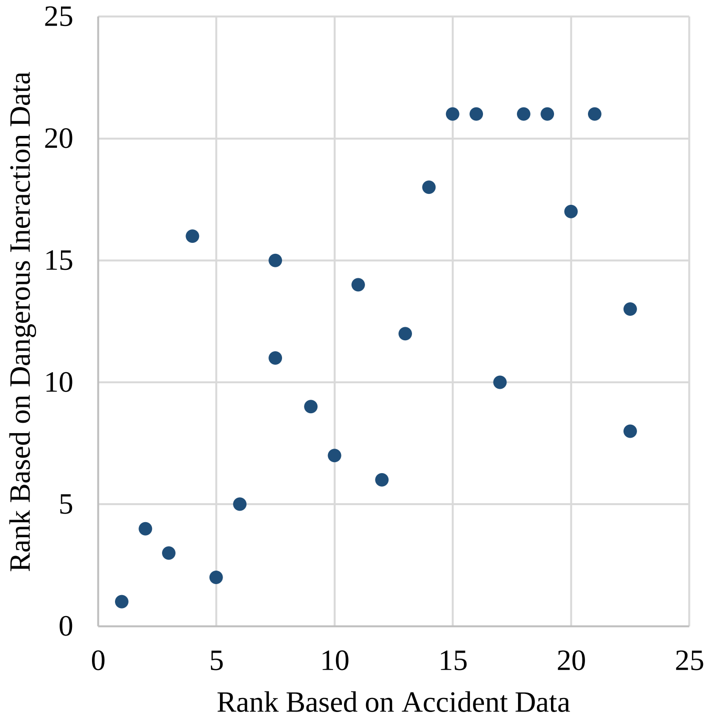

Figure 7. Comparison between the ranking based on accident data and the ranking based on interaction data

Spearman's rank correlation coefficient is a nonparametric measure of statistical dependence between two variables. It assesses how well the relationship between two variables can be described using a monotonic function. A perfect Spearman correlation of +1 or −1 occurs when each of the variables is a perfect monotone function of the other. Spearman’s rank correlation can be computed as follows:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{3}$$

Where n is the number of samples and d_i is the difference between the ranks for measure (site) i based on the two safety measures. Note that identical values (rank ties or value duplicates) are assigned a rank equal to the average of their positions in the ascending order of the values. Using this definition, Spearman’s correlation between the ranks based on accident data and dangerous interaction data was 0.64 which shows a high correlation between accident data and dangerous interactions.

Other than using just AADB in equation (2), other values such as AADB multiplied by AADT and AADB multiplied by AADTT were applied, where AADT is the average annual daily vehicle traffic and AADTT is the average annual daily turning vehicle traffic at an intersection. In addition to using t equal to 1.5 seconds, t equal to five seconds was also tested to find the best surrogate measure of safety (Table 5). Furthermore, using AADB and the Empirical Bayes (EB) estimation of accidents in equation (2), resulted in a correlation of 0.55 with ranks based on interactions with surrogate measures with t equal to 1.5 seconds. Although all of these results had relatively acceptable correlation values, the use of *t* equal to 1.5 seconds in equation (1), and using just AADB as the exposure measure in equation (2), resulted in the highest correlation value.

Table 5. Spearman's rank correlation for different interactions and exposure measures

Interaction and PET threshold \ Exposure measure	AADB	AADB * AADT	AADB * AADTT
NPET with t = 1.5 s	0.64	0.40	0.45
NPET with t = 5 s	0.35	0.33	0.45

Also a linear correlation of 0.4 between the number of accidents per year and the hourly number of very dangerous interactions (with PET lower than 1.5 s) is obtained. This again shows some evidence about the relationship between reported accidents and the surrogate safety indicator used in this study. This relationship however needs more investigation using more data (longer periods of time and more sites).

6. CONCLUSION AND FUTURE WORK

This research investigated the safety effectiveness of cycle tracks using a cyclist-vehicle interaction methodology based on an automated video process. PET is used as a surrogate safety measure for defining the severity of interactions between cyclists and turning vehicles. The proposed methodology consisted of three main steps: i) video data collection at the selected treated and control sites, ii) automatic road user detection, tracking and classification, as well as the computation of PET between cyclists and turning vehicles, and iii) statistical modeling of PET values to identify the effects of cycle tracks and other variables on cyclist safety.

Empirical evidence is generated based on a relatively large sample of intersections with many hours of video data. A total of 23 intersections were involved, eight with a cycle track on the right side, seven with a cycle track on the left side, and eight without a cycle track. From over 90 hours of video, over 7,000 cyclists were recorded and used in this study. Each cyclist and its interaction with turning vehicles represents an observation in the random effects ordered logit modeling framework. Different models were fitted to the data in order to compare the safety effects of intersections in the presence and absence of cycle tracks. In addition to presence of cycle tracks and their locations, measures of traffic conditions and geometry were also evaluated using statistical analysis.

Among other results, interaction rates estimated from the raw data showed that intersections with cycle tracks on the right or left side appear to be safer than no cycle track. However, these results do not account for disaggregate traffic flow conditions and geometry characteristics. Therefore, a regression analysis was executed. Based on the recorded video data and our analysis, it seems that intersections with cycle tracks on the right, compared to intersections with no cycle track are safer. By adding a cycle track to the right side of intersections currently without a cycle track, interactions (with PET $\leq$ 5 s) are expected to drop by around 40 %. However, cycle tracks on the left did not show any significant decrease in the probability of interactions compared to no cycle tracks. Cycle tracks on the right are then recommended, from a safety perspective, over cycle tracks on the left. Building cycle tracks on the right side is associated with 25 % fewer interactions (with PET $\leq$ 5 s) than on the left side. Ideally intersection treatments should be implemented as well, in addition to having cycle tracks, to ensure the safety provided by cycle tracks along road segments is not overruled by interactions and the potential for collisions they may cause at intersections.

Other factors such as bicycle and turning vehicle flows in the few seconds before and after the arrival of each cyclist to the intersection were shown to have a statistically significant effect on interactions between cyclists and turning vehicles. These micro-level exposure measures provide a better understanding of cyclist behaviours and interaction mechanisms. For instance, the effect of cyclists arriving alone or in a group was evaluated. Interaction severity was found to reduce as cyclist presence increases (size of group arriving at the intersection). An opposite effect was observed for turning vehicles, more traffic results in a higher probability of serious interactions. Some geometry factors such as the number of lanes were also shown to be statistically significant. More lanes in the vehicle approach result in more dangerous situations for cyclists. This means that in addition to the installation of right-side cycle tracks, the reduction of vehicle turning movements and geometry changes could represent additional safety benefits. These results highlight the important role that cycle tracks play in cyclist safety and reinforce the findings reported using the traditional safety approach.

It is also important to recognize that a before-after observational approach is more suitable than control case-studies to evaluate safety treatments. However, the before-after approach is difficult to implement when safety treatments have already been implemented and when no data from the before period is available – which is the case in this research. As part of the future work, the effectiveness of cycle tracks needs to be evaluated using longitudinal before-after surrogate approach. Another limitation of this work is the small number of hours of recorded video from each site. By recording video for longer periods of time from fewer intersections, the safety effect of cycle tracks can be confirmed.

Also, as part of future work, the safety effect of cycle tracks at non-signalized intersections will be investigated. Other interactions will also be examined such as cyclist-vehicle rear-end interactions and pedestrian-cyclist interactions in shared spaces. The proposed methodology could also be replicated to validate the safety effectiveness of different bicycle facility designs (bidirectional vs unidirectional, bicycle lanes, etc.). This could also involve different cities and longitudinal video data. This will help provide a more general and transferable results about the safety effectiveness of bicycle facilities. In addition, by recording video for a longer period of time, one will be able to investigate the safety effect of cycle tracks for different times of the day (including nighttime). To test the accuracy of surrogate safety measures as an indicator of accidents and injuries, these results will be compared to historical accident and injury data. Another study will be carried out to compare the safety effects of unidirectional versus bidirectional cycle tracks. Also the safety effect of different signal phasing, including advanced green light for cyclists and pedestrians, will be investigated.

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REFERENCES

Afghari, A.P. et al., 2014. Pedestrian-cyclist Interactions at Bus Stops along Segregated Bike Paths: A Case Study of Montreal. In *Transportation Research Board 93rd Annual Meeting*.

Anderson-Trocmé, P., Stipancic, J. & Miranda-Moreno, L.F., 2015. Performance Evaluation and Error Segregation of Video-Collected Traffic Speed Data. *94th Transportation Research Board Annual Meeting*.

Chen, L. et al., 2012. Evaluating the safety effects of bicycle lanes in New York City. *American journal of public health*, 102(6), pp.1120–7. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22095351 [Accessed July 8, 2013].

Crouchley, R., 1995. A Random-Effects Model for Ordered Categorical Data. *Journal of the American Statistical Association*, 90(430), p.489. Available at: http://www.jstor.org/stable/2291059?origin=crossref [Accessed November 5, 2014].

Dill, J., Monsere, C.M. & McNeil, N., 2012. Evaluation of bike boxes at signalized intersections. *Accident; analysis and prevention*, 44(1), pp.126–34. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22062346 [Accessed July 24, 2014].

Gårder, P., Leden, L. & Pulkkinen, U., 1998. Measuring the Safety Effect of Raised Bicycle Crossings Using a New Research Methodology. *Transportation Research Record*, 1636(1), pp.64–70. Available at: http://trb.metapress.com/index/B150T4W7641755H5.pdf [Accessed November 6, 2014].

Gårder, P., Leden, L. & Thedéen, T., 1994. Safety implications of bicycle paths at signalized intersections. *Accident Analysis & Prevention*, 26(4), pp.429–439. Available at: http://linkinghub.elsevier.com/retrieve/pii/0001457594900345 [Accessed November 6, 2014].

Gettman, D. & Head, L., 2003. Surrogate Safety Measures from Traffic Simulation Models. *Transportation Research Record*, 1840(1), pp.104–115. Available at: http://trb.metapress.com/index/T264J4213G6V863Q.pdf [Accessed July 19, 2012].

Jacobsen, P.L., 2003. Safety in numbers: more walkers and bicyclists, safer walking and bicycling. *Injury Prevention*, 9(3), pp.205–209. Available at: http://ip.bmj.com/cgi/doi/10.1136/ip.9.3.205 [Accessed July 24, 2014].

Jensen, S., 2008. Bicycle tracks and lanes: A before-after study. *87th Annual Meeting of the Transportation Research Board*, (August). Available at: http://www.ibiketo.ca/sites/default/files/bicycle tracks and lanes.pdf [Accessed July 24, 2014].

Jensen, S.U., 2008. Safety effects of blue cycle crossings: a before-after study. *Accident; analysis and prevention*, 40(2), pp.742–50. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18329429 [Accessed September 16, 2013].

Kassim, A., Ismail, K. & Hassan, Y., 2014. Automated measuring of cyclist – motor vehicle post encroachment time at signalized intersections. *Canadian Journal of Civil Engineering*, 41(7), pp.605–614. Available at: http://www.nrcresearchpress.com/doi/abs/10.1139/cjce-2013-0565.

Laureshyn, A. et al., 2009. Application of automated video analysis for behavioural studies: concept and experience. *IET Intelligent Transport Systems*, 3(3), p.345. Available at: http://digital-library.theiet.org/content/journals/10.1049/iet-its.2008.0077 [Accessed November 6, 2014].

Laureshyn, A., Svensson, Å. & Hydén, C., 2010. Evaluation of traffic safety, based on micro-level behavioural data: Theoretical framework and first implementation. *Accident Analysis and Prevention*, 42(6), pp.1637–1646. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20728612 [Accessed November 6, 2014].

Lusk, A.C. et al., 2011. Risk of injury for bicycling on cycle tracks versus in the street. *Injury prevention : journal of the International Society for Child and Adolescent Injury Prevention*, 17(2), pp.131–5. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3064866&tool=pmcentrez&rendertype=abstract [Accessed July 24, 2014].

Miranda-Moreno, L.F., Strauss, J. & Morency, P., 2011. Disaggregate Exposure Measures and Injury Frequency Models of Cyclist Safety at Signalized Intersections. *Transportation Research Record*, 2236, pp.74–82.

Mohamed, M.G. & Saunier, N., 2013. Motion Prediction Methods for Surrogate Safety Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, 2386, pp.168–178. Available at: http://trb.metapress.com/openurl.asp?genre=article&id=doi:10.3141/2386-19 [Accessed March 5, 2014].

Phillips, R.O. et al., 2011. Reduction in car–bicycle conflict at a road–cycle path intersection: Evidence of road user adaptation? *Transportation Research Part F: Traffic Psychology and Behaviour*, 14(2), pp.87–95. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1369847810000859 [Accessed July 24, 2012].

Reynolds, C.C.O. et al., 2009. The impact of transportation infrastructure on bicycling injuries and crashes: a review of the literature. *Environmental health : a global access science source*, 8, p.47. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2776010&tool=pmcentrez&rendertype=abstract [Accessed July 21, 2014].

Sakshaug, L. et al., 2010. Cyclists in roundabouts--different design solutions. *Accident; analysis and prevention*, 42(4), pp.1338–51. Available at: http://www.sciencedirect.com/science/article/pii/S0001457510000606 [Accessed July 9, 2014].

Saunier, N., Traffic Intelligence. Available at: https://bitbucket.org/Nicolas/trafficintelligence/ [Accessed January 1, 2013].

Saunier, N. & Sayed, T., 2006. A feature-based tracking algorithm for vehicles in intersections. *The 3rd Canadian Conference on Computer and Robot Vision (CRV'06)*, pp.59–59. Available at: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1640414 [Accessed July 22, 2013].

Sayed, T., Zaki, M.H. & Autey, J., 2013a. Automated safety diagnosis of vehicle–bicycle interactions using computer vision analysis. *Safety Science*, 59, pp.163–172. Available at: http://www.sciencedirect.com/science/article/pii/S0925753513001240 [Accessed July 25, 2014].

Sayed, T., Zaki, M.H. & Autey, J., 2013b. Automated safety diagnosis of vehicle–bicycle interactions using computer vision analysis. *Safety Science*, 59, pp.163–172. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0925753513001240 [Accessed July 25, 2014].

St-Aubin, P., Saunier, N. & Miranda-Moreno, L., 2015. Large-scale automated proactive road safety analysis using video data. *Transportation Research Part C: Emerging Technologies*. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0968090X15001485.

Strauss, J., Miranda-Moreno, L.F. & Morency, P., 2013. Cyclist activity and injury risk analysis at signalized intersections: A Bayesian modelling approach. *Accident Analysis and Prevention*, 59, pp.9–17. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0001457513001905 [Accessed May 23, 2013].

Strauss, J., Miranda-Moreno, L.F. & Morency, P., 2013. Cyclist activity and injury risk analysis at signalized intersections: a Bayesian modelling approach. *Accident; analysis and prevention*, 59, pp.9–17. Available at: http://www.ncbi.nlm.nih.gov/pubmed/23743297 [Accessed July 24, 2014].

Strauss, J., Miranda-Moreno, L.F. & Morency, P., 2015. Mapping Cyclist Activity and Injury Risk in a Network Combining Smartphone GPS Data and Bicycle Counts. In *Transportation Research Board 94th Annual Meeting*.

Teschke, K. et al., 2012. Route infrastructure and the risk of injuries to bicyclists: a case-crossover study. *American journal of public health*, 102(12), pp.2336–43. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3519333&tool=pmcentrez&rendertype=abstract [Accessed July 25, 2014].

Thomas, B. & DeRobertis, M., 2013. The safety of urban cycle tracks: a review of the literature. *Accident; analysis and prevention*, 52, pp.219–27. Available at: http://www.ncbi.nlm.nih.gov/pubmed/23396201 [Accessed July 21, 2014].

Vogel, K., 2003. A comparison of headway and time to collision as safety indicators. *Accident Analysis & Prevention*, 35(3), pp.427–433. Available at: http://www.sciencedirect.com/science/article/pii/S0001457502000222 [Accessed October 26, 2014].

Wang, Y. & Nihan, N.L., 2004. Estimating the risk of collisions between bicycles and motor vehicles at signalized intersections. *Accident analysis and prevention*, 36, pp.313–321.

Zangenehpour, S., 2013. Impact of bicycle boxes on safety of cyclists: a case study in Montreal. *Transportation Research Board 92nd Annual Meeting*. Available at: http://trid.trb.org/view.aspx?id=1241733 [Accessed July 24, 2014].

Zangenehpour, S., Romancyshyn, T., et al., 2015. Video-Based Automatic Counting For Short-Term Bicycle Data Collection in a Variety of Environments. *94th Transportation Research Board Annual Meeting*.

Zangenehpour, S., Miranda-Moreno, L.F. & Saunier, N., 2015. Automated classification based on video data at intersections with heavy pedestrian and bicycle traffic: Methodology and application. *Transportation Research Part C: Emerging Technologies*.

Zangenehpour, S., Miranda-Moreno, L.F. & Saunier, N., 2014. Automated classification in traffic video at intersections with heavy pedestrian and bicycle traffic. *Transportation Research Board Annual Meeting*.