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1 **INVESTIGATING THE EFFECTS OF GENDER ON BICYCLE-VEHICLE CONFLICTS AT**
2 **URBAN INTERSECTIONS USING AN ORDERED LOGIT METHODOLOGY**

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1 ABSTRACT

2 In the literature, a crash-based modeling approach has long been used to evaluate the factors that contribute
3 to cyclist injury risk at intersections. However, this approach has been criticized as crashes are required to
4 occur before contributing factors can be identified and countermeasures can be implemented. Moreover,
5 human factors related to dangerous behaviors are difficult to evaluate using crash-based methods. As an
6 alternative, surrogate safety measures have been developed to address the issue of reliance on crash data.
7 Despite recent developments, few methodologies and little empirical evidence exist on bicycle-vehicle
8 interactions at intersections using video-based data and statistical analyses. This study investigates bicycle-
9 vehicle conflict severity and evaluates the impact of different factors, including gender, on cyclist risk at
10 urban intersections with cycle tracks. A segmented ordered logit model is used to evaluate post-
11 encroachment time between cyclists and vehicles. Video data was collected at seven intersections in
12 Montreal, Canada. Road user trajectories were automatically extracted, classified, and filtered using a
13 computer vision software to yield 1,514 interactions for analysis. The discrete choice variable was created
14 by dividing post-encroachment time into normal interactions, conflicts, and dangerous conflicts.
15 Independent variables reflecting attributes of the cyclist, vehicle, and environment were extracted either
16 automatically or manually. Results indicated that an ordered model is appropriate for analyzing traffic
17 conflicts. Furthermore, exogenous segmentation was beneficial in comparing different segments of the
18 population within a single model. Male cyclists, with all else being equal, were less likely than female
19 cyclists to be involved in conflicts and dangerous conflicts at the studied intersections. Bicycle and vehicle
20 speed, along with the time of the conflict relative to the red light phase, were other significant factors in
21 conflict severity. These results will contribute to and further the understanding of gender differences in
22 cycling within North America.

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27 *Keywords:* discrete choice; cycling; surrogate safety; gender; urban; order logit

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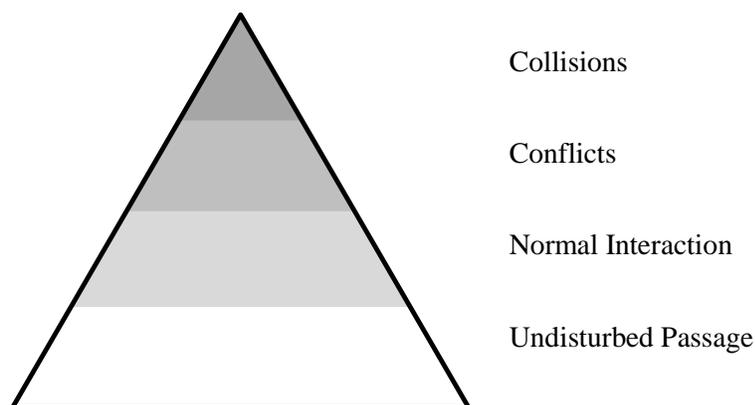
1 INTRODUCTION

2 Road safety is a substantial concern for transportation professionals due to the high economic and social
 3 cost of traffic crashes (Abdel-Aty, 2003). In 2012, traffic crashes resulted in 2077 fatalities and over
 4 165,000 injuries in Canada, where cyclists and pedestrians account for approximately 18% of both fatalities
 5 and injuries annually (Transport Canada, 2014). While the safety of motorists has commanded much
 6 attention, the protection of vulnerable road users has become common only recently (Kockelman & Kweon,
 7 2002). In North America, cyclists are twelve times more likely to be killed than motor vehicle drivers
 8 (Moore, Schneider IV, Savolainen, & Farzanah, 2011; Strauss, Miranda-Moreno, & Morency, 2014), and
 9 269 cyclist fatalities occurred in Canada between 2008 and 2012 (Transport Canada, 2014).

10 Recent growth in bicycle activity and infrastructure improvement have increased awareness of
 11 bicycle safety issues in North America. In this context, the complex nature of cyclist-vehicle interactions
 12 must be understood by examining the factors that contribute to cyclist safety (Klop & Khattak, 2007;
 13 Moore, Schneider IV, Savolainen, & Farzanah, 2011). One method for evaluating these factors is traffic
 14 crash modelling. Crash models evaluate collision frequency using count regression models, or crash injury
 15 severity using different techniques such as ordered logit, discrete choice regression models, and tree-based
 16 or neural network techniques. Many studies have considered the different statistical methods available. A
 17 recent summary of literature on crash frequency and severity modelling is provided by Mannering and Bhatt
 18 (2014). Additional summaries were compiled by Miranda-Moreno (2006), Lord and Mannering (2010), and
 19 Savolainen et al. (2011). Traditional safety models calibrated with crash data are reactive, requiring crashes
 20 to occur before causes can be identified and countermeasures can be implemented. Additionally, crash-
 21 based methods require long observation periods. Given the low rate of crash occurrence, many years of
 22 accident data are required. Finally, the study of dangerous behaviors and other human factors can often not
 23 be investigated.

24 As an alternative or complementary approach, surrogate safety techniques analyze interactions and
 25 conflicts rather than crashes. Conflicts are events that are physically and predictably related to traffic
 26 crashes, and are placed immediately below collisions in Hyden's model (Hyden, 1987), presented in
 27 FIGURE 1. As the pyramid model suggests, traffic interactions are inherently ordered through their
 28 proximity to a potential collision, or severity, as measured by various indicators. Modelling interactions
 29 rather than collisions provides several benefits. Interactions occur much more frequently than collisions
 30 and statistically sufficient data can be collected in a shorter time period. The use of interactions and conflicts
 31 is proactive, rather than reactive, and surrogate measures are insensitive to crash underreporting
 32 (Kockelman & Kweon, 2002) and human factors can be incorporated in the analysis.

33



34

35

36 **FIGURE 1 Safety pyramid based on Hyden's classic model (Hyden, 1987)**

37 Despite the benefits offered by a proactive surrogate approach, dangerous bicycle behaviours in
 38 vehicle-bicycle interactions, and their associated factors, have rarely been studied using video analysis,

1 surrogate measures of safety, and regression models. A particular issue that remains to be investigated using
2 microscopic conflict data is the relationship between biological gender and cyclist safety. Important
3 behavioral differences have been identified for both pedestrians and motorists of different genders at
4 intersections (Holland & Hill, 2007; Santamarina-Rubio, Perez, Olabarria, & Novoa, 2014; Tom & Granie,
5 2011). However, very little is known about this in the cyclist context. Gender differences and their
6 associated risks may help to explain the disparity in ridership currently experienced in urban populations
7 as well as the implementation of the appropriate designs and facilities. In most countries, females cycle less
8 than males, particularly in English speaking countries that are less bicycle-friendly, including Canada, the
9 U.K., Australia, and the U.S. (Garrard, Handy, & Dill, 2012). Route conditions and vehicle interactions
10 greatly influence individuals' likelihood to cycle (Winters, Davidson, Kao, & Teschke, 2011) and female
11 cyclists, much more than males, prefer to use routes with maximum separation from motorized traffic
12 (Garrard, Rose, & Lo Kai, 2008). Studies in the city of Montreal show that routes with separated cycle
13 tracks attract higher cyclist volumes than those without (Strauss & Miranda-Moreno, 2013) and that streets
14 with cycle tracks have a lower injury risk (Lusk, et al., 2011).

15 While behavioural differences may exist between genders, recent research has only shown minor
16 differences in actual crash risk for males and females (Kaplan, Vavatsoulas, & Prato, 2014; Martinez-Ruiz,
17 et al., 2014). The purpose of this study is to estimate a segmented ordered logit model for bicycle-vehicle
18 interactions at urban intersections with cycle tracks. Intersections, being one of the most dangerous
19 locations in the urban network, deserve specific attention (Wang & Abdel-Aty, 2008). The objectives of
20 this research are to investigate bicycle-vehicle conflicts and contributory factors using an ordered-logit
21 modelling approach and to examine the influence of gender and other cyclist, vehicle, and environmental
22 factors on conflict severity.

23 24 **LITERATURE REVIEW**

25 Existing efforts in injury severity modelling primarily concern motor vehicle occupants in single or multiple
26 vehicle crashes. Multiple modeling techniques have been proposed to investigate the relationship between
27 injury severity levels and associated factors. Mannering and Bhatt (2014) provide a comprehensive
28 literature review on the methods used in severity analysis in general, and Eluru et al. (2008) provides a
29 summary of literature concerning analysis of cyclist injuries. Much empirical evidence has been reported
30 in the literature identifying the key factors influencing injury severity, including characteristics of the
31 roadway, environment, and road user, for passengers, drivers and pedestrians. Moore et al. (2011) utilized
32 a multinomial logit and mixed logit to model cyclist injury severity at intersections and non-intersection
33 locations using seven years of crash data from Ohio. The study stated "the injury mechanisms are
34 substantially different [...] at intersection and non-intersection locations". Klop and Khattak (2007) studied
35 bicycle crash severity on rural roads in North Carolina using an ordered probit model and four years of
36 crash data. Visibility and weather conditions were found to most significantly increase collision severity.
37 Eluru et al. (2008) utilized data from the 2004 US national database to estimate a mixed generalized ordered
38 response logit (MGORL) model of cyclist injury severity. The MGORL generalizes more standard ordered
39 models, providing additional flexibility across observations. Cyclist age and vehicle speed were correlated
40 with injury severity. In the existing literature, gender is often a contributory factor to injury severity.

41 Cyclist gender studies have focussed largely on variation in preference or behaviour. Bernhoft and
42 Carstensen (2008) used a survey approach, finding that male cyclists in Denmark tended to act less
43 cautiously, but also felt safer than their female counterparts. However, many of the differences between
44 genders became statistically insignificant when controlling for other factors, such as travel patterns, which
45 may themselves be gender specific. Similarly, a French study by Felonneau et al. (2013) noted that male
46 cyclists tended to overestimate their ability more so than females whereas females tend to overestimate
47 their carefulness more than males and proneness to take risk as cyclist seems to be gender specific even at
48 an early age (Granié, 2011). Johnson, Newstead, Charlton, and Oxley (2011) studied red-light compliance
49 and found that male cyclists were more frequently non-compliant than females. While gender differences
50 are evident in terms of behaviour, behavioural differences do not necessarily create disparity in risk. Kaplan
51 et al. (2014) evaluated injury severity using a generalized ordered logit model on Danish crash data

1 collected over a 5-year period, and found no correlation between gender and injury risk. Martinez-Ruiz et
2 al. (2014) used 17 years of crash data from Spain to calculate the crash rate ratio by gender for different
3 ages. Without adjusting for cycling exposure, males were more likely to be involved in a collision than
4 females. When controlling for exposure, crash rates were approximately equal for males and females with
5 age being a stronger determinant of crash risk. As female cyclists seem to favour sites with cycle tracks
6 (Garrard, Rose, & Lo Kai, 2008) a possible explanation for this lack of difference in the risk of accidents
7 can be found in the behavior of male and female cyclists on road with cycle tracks.

8 While research on severity modelling includes consideration for cyclists and advanced
9 formulations, few studies have attempted to apply modeling techniques to surrogate measures for bicycle
10 safety (Zangenehpour, Miranda-Moreno, & Saunier, 2013; Zangenehpour, Strauss, Miranda-Moreno, &
11 Saunier, 2015). Analysis of differences between male and female cyclist risk by surrogate safety techniques
12 has also been limited. Rather than using independent models for males and females, a segmented modelling
13 approach is preferred in order to increase the number of observations available for estimation and to make
14 differences between genders instantly comparable. The reliance on crash data has meant dependence on
15 crash databases, which are subject to underreporting, errors, and omissions. This study attempts to address
16 these shortcomings through the estimation of a segmented ordered logit model of interaction severity.

17 18 **METHODOLOGY**

19 The methodology consists of three steps; video data collection and processing using video tracking and
20 classification methods; definition and computation of surrogate safety indicators, and; model formulation
21 and estimation. The details of each step are provided in the following sections.

22 23 **Video Data Collection and Processing**

24 The methodology for data collection and processing uses a similar approach to the one implemented in
25 several past studies (Jackson, Miranda-Moreno, St-Aubin, & Saunier, 2013; Saunier, Sayed, & Ismail,
26 2010; Sayed, Zaki, & Autey, 2013) . Video data was collected using an inexpensive and commercially
27 available video camera which stores video and is powered internally. The camera is mounted to a using a
28 telescoping fibreglass mast to ensure a clear view above the intersection and approaches. The camera system
29 is introduced in detail by Zangenehpour, Miranda-Moreno, & Saunier (2015). Once collected, the video
30 data was processed using an open-source road user tracking software, Traffic Intelligence (Jackson,
31 Miranda-Moreno, St-Aubin, & Saunier, 2013; Saunier, Sayed, & Ismail, 2010; Saunier, 2015). Road user
32 trajectories (position and speed at each frame) were automatically extracted from the video footage. Road
33 users were then classified as pedestrians, cyclists, or vehicles using a technique developed by
34 Zangenehpour, Miranda-Moreno, and Saunier (2014), and the trajectories were filtered to isolate the desired
35 interactions. Any erroneous interactions were removed manually from the data set.

36 37 **Computation of Surrogate Safety Measures**

38 Popular surrogate measures of safety include time-to-collision (TTC) and post-encroachment time (PET).
39 TTC is “the time required for two vehicles to collide if they continue at their present speed and on the same
40 path” (van der Horst, de Goede, de Hair-Buijssen, & Methorst, 2014) or more generally if their movements
41 remain unchanged, which can include variations in speed and direction. PET is the difference in time
42 between two road users occupying the same location in space, or the potential conflict point (Peesapati,
43 Hunter, & Rodgers, 2013). TTC is measured continuously and, depending on the choice or motion
44 prediction method, will yield several measurements over time when there is a collision course (when some
45 predicted trajectories would lead the road users to collide). PET is based on observed trajectories and can
46 be computed only if trajectories intersect. Both measures can usually be computed for the same interaction
47 and are complementary in the analysis of bicycle conflicts (van der Horst, de Goede, de Hair-Buijssen, &
48 Methorst, 2014). Surrogate safety data has been successfully collected using video-based detection systems
49 and extracted using computer vision techniques (Jackson, Miranda-Moreno, St-Aubin, & Saunier, 2013;
50 Sayed, Zaki, & Autey, 2013). PET was selected as the surrogate measure of safety in this research as all
51 interactions involve intersecting trajectories. PET is better suited to interactions involving turning

1 movements than common TTC with assumption of constant velocity and it is simpler and faster to compute
2 than TTC with more realistic motion prediction methods.

3 Once trajectories were extracted using Traffic Intelligence, PET calculation for each interaction
4 was automated using a Python script to count the number of frames (converted to seconds) between
5 consecutive road users occupying the conflict point. The dependent choice variable was created by
6 classifying PET as:

- 7
- 8 • Alternative 0: Normal interaction with PET greater than 5 seconds;
- 9 • Alternative 1: Conflict with PET between 3 and 5 seconds, and;
- 10 • Alternative 2: Dangerous conflict with PET less than 3 seconds.

11
12 These thresholds have been used successfully in previous work, such as Zangenehpour, Strauss, Miranda-
13 Moreno, & Saunier (2015), where readers are referred for more details on the determination of threshold
14 values. This formulation yields results that are easy to interpret, as positive coefficients indicate an increase
15 in the severity of conflicts (decrease in PET) as the variable associated with that coefficient increases
16 (Kockelman & Kweon, 2002).

19 **Modelling Framework Definition and Model Estimation**

20 Ordered response models are the most widely used statistical models in crash severity analysis. Unlike other
21 multiple choice models that include utility variables for each alternative, ordered models have only one
22 propensity, or latent variable (O'Donnell & Connor, 1996). The ordered logit model assumes that the error
23 term, representing the unobserved component of the latent variable, is logistic distributed with a mean of
24 zero and a variance of $\pi^2/3$. The latent variable, y^* , is defined by

$$25 \quad y^* = \beta X + \varepsilon \quad (1)$$

26
27 where X is the vector of explanatory variables, β is the vector of unknown parameters, and ε is the logistic
28 distributed random error term. This propensity is bound by unknown thresholds, τ_i , which delineate
29 alternatives. For the case presented herein, the probability of each choice alternative is

$$30 \quad \begin{aligned} 31 \quad P(y=0) &= CDF(\tau_1 - \beta X) \quad (\text{normal interaction}) & (2) \\ 32 \quad P(y=1) &= CDF(\tau_2 - \beta X) - CDF(\tau_1 - \beta X) \quad (\text{conflict}) \\ 33 \quad P(y=2) &= 1 - CDF(\tau_2 - \beta X) \quad (\text{serious conflict}) \end{aligned}$$

34
35 where CDF is the cumulative distribution function of the logistic distribution defining ε .

36 Exogenous segmentation is a method that provides heterogeneity in the coefficients across multiple
37 segments, working particularly well when segments are few (Bhat, 1997). For this study, segmentation
38 allows for variation in the value of the parameters across cyclist gender. Segmentation is achieved through
39 the generation of new independent segmented variables, which are the product of the existing independent
40 variables and some discrete variable (gender). When the model is estimated, the parameter on the basic
41 variables represents a contribution to both genders, while the parameters on the segmented variables
42 represent the variation between genders. The propensity for the segmented model can be represented by

$$43 \quad y^* = \beta_1 X + \beta_2 w X + \beta_3 w + \varepsilon \quad (3)$$

44
45 where X are the basic variables and β_1 are their coefficients, $w X$ and β_2 are the segmented variables and
46 their coefficients, respectively, and w and β_3 are the segmentation variable (gender) and its coefficient,
47 respectively.

48 The conflict severity model was developed in three steps, with each step incorporating additional
49 gender heterogeneity. An ordered logit model (OL1) was estimated assuming homogeneity between
50
51

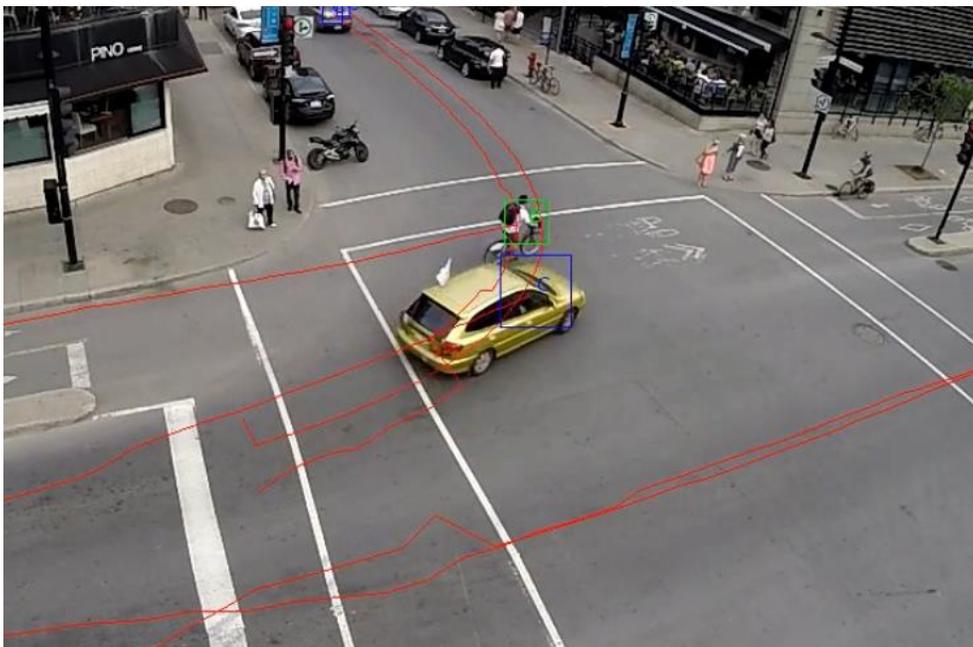
1 genders. This model included all available variables without consideration for gender. With the addition of
2 the gender, OL2 was created. The inclusion of this variable introduced simplistic heterogeneity, by allowing
3 the latent propensity to change according to cyclist gender. The final segmented ordered logit model (SOL)
4 included all available explanatory variables with segmentation according to gender. This allowed not only
5 the propensity, but also the value of each parameter, to vary between genders. While similar results can be
6 achieved through the estimation of separate models, segmentation increases the number of observations for
7 estimation and makes differences between genders instantly comparable.
8

9 DATA DESCRIPTION

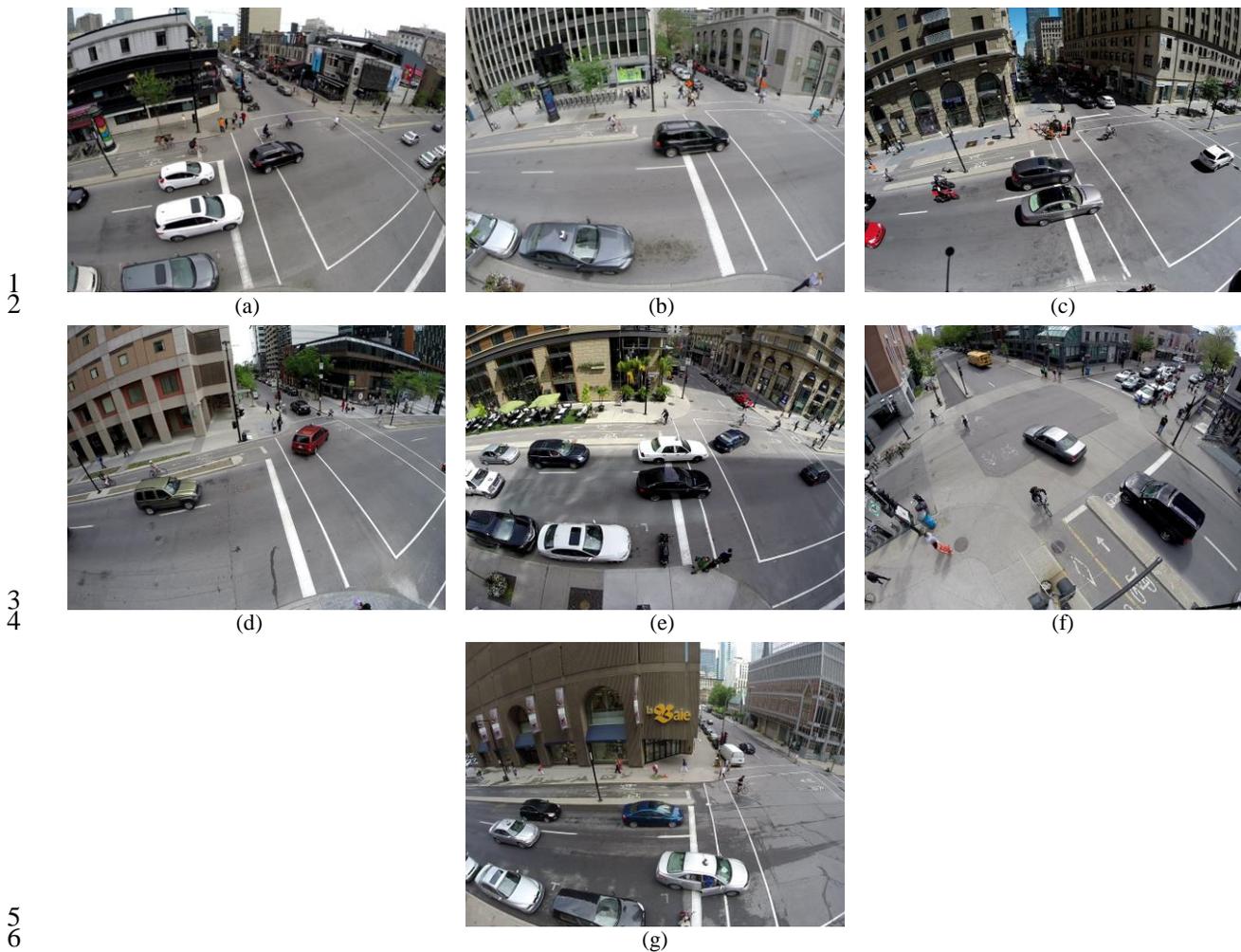
11 Site Selection

12 Seven test sites were selected along Maisonneuve Boulevard, a one-way urban arterial in downtown
13 Montreal, Canada. The sites, shown in FIGURE 3, featured two travel lanes and a fully separated
14 bidirectional cycling facility, or cycle track, along Maisonneuve. The sites along Maisonneuve were
15 selected specifically because of the present cycling infrastructure. The two-way separated cycle track is a
16 relatively new design that has only been studied more recently. Maisonneuve is also one of the busiest
17 cycling corridors on the island of Montreal, and the specific intersections were chosen because of their
18 geometric uniformity. On all the observed intersections, the cycling lane is on the left of the two other travel
19 lanes. Video data was collected using a single camera at each site with a clear view above the intersection.
20 Approximately 4 hours of video was collected at each site in the afternoon peak period from June 16 to
21 June 20, 2014, ensuring that traffic volume, weather, time of year, and time of day remained consistent.

22 Similar to Wang and Abdel-Aty (2008), a single traffic interaction was analyzed. Conflicts were
23 limited to those between cyclists traveling straight through the intersection and left-turning vehicles. An
24 example of a dangerous conflict is provided in FIGURE 2. Given the site geometry and design of the cycling
25 infrastructure, these interactions represent the majority of safety concerns since cyclists wishing to go
26 through the intersection should consider vehicles located on their right wishing to turn left. Any erroneous
27 interactions were removed manually from the data set. Several interactions were also missed by the tracking
28 algorithm, which could not be included as part of this study. Once filtered, 1514 useable observations
29 remained for analysis.
30



31
32 **FIGURE 2 Example of a dangerous bicycle-vehicle conflict**



7 **FIGURE 3 Study sites along Maisonneuve at Crescent (a), Stanley (b), Peel (c), Mackay (d),**
8 **Metcalfe (e), St Denis (f), and Union (g)**

9 **Data Exploration**

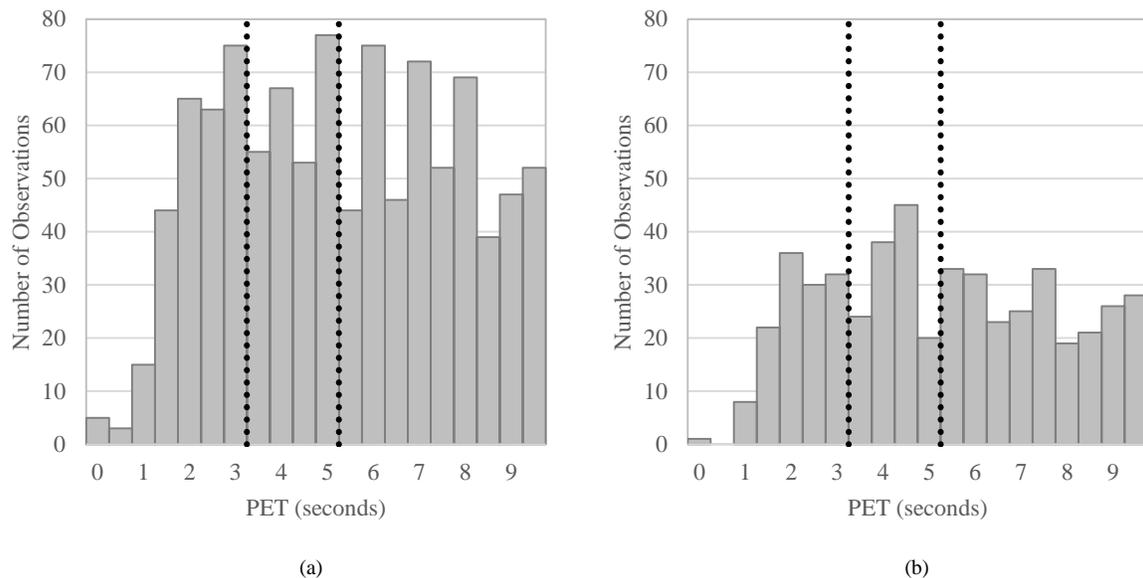
10 Attributes of the cyclist, vehicle, and environment were compiled as independent variables. Cyclist and
11 vehicle speed at the conflict point were automatically computed from the trajectories. Additional
12 explanatory variables, including cyclist gender helmet use, whether the vehicle was a truck, van, or SUV,
13 and whether the vehicle was the first in a platoon, were extracted manually from the video. As in previous
14 studies (Johnson, Newstead, Charlton, & Oxley, 2011), gender was classified based on physical appearance.
15 The environmental attributes included variables representing if the interaction occurred immediately after
16 a red light phase (both cyclist and vehicle were simultaneously waiting at a red light before the interaction
17 occurred) and site-specific constants for each site, with Crescent used as the reference. Dummy variables
18 were used to indicate whether the cyclist was the first object to reach the conflict point and whether
19 pedestrians (or contra-flow cyclists) were present in the intersection at the time of the conflict, capturing
20 the behavioural freedom of the road users. A summary is provided in TABLE 1. Site specific data has been
21 omitted for brevity.

22

1 **TABLE 1 Variables and Statistics for All Captured Interactions**

	Units	Description	Mean	Min.	Max.	Std. Dev.
Cyclist						
Speed	km/h	Speed of the cyclist at the conflict point	13.16	1.71	43.51	5.39
Male	Dummy	Cyclist was male (1) or female (0)	0.67	0	1	0.47
Helmet	Dummy	Cyclist wearing a helmet (1) or not (0)	0.51	0	1	0.50
Vehicle						
Speed	km/h	Speed of the vehicle at the conflict point	20.01	2.00	67.10	6.43
Platoon Lead	Dummy	Vehicle was first in a platoon	0.76	0	1	0.43
Truck	Dummy	Vehicle was a truck, van, or SUV	0.33	0	1	0.47
Environment						
Red	Dummy	Conflict occurred immediately after a red light	0.16	0	1	.365
Bike First	Dummy	The cyclist reached the conflict point first	0.59	0	1	.493
Pedestrian	Dummy	Peds were simultaneously crossing intersection	0.46	0	1	.499

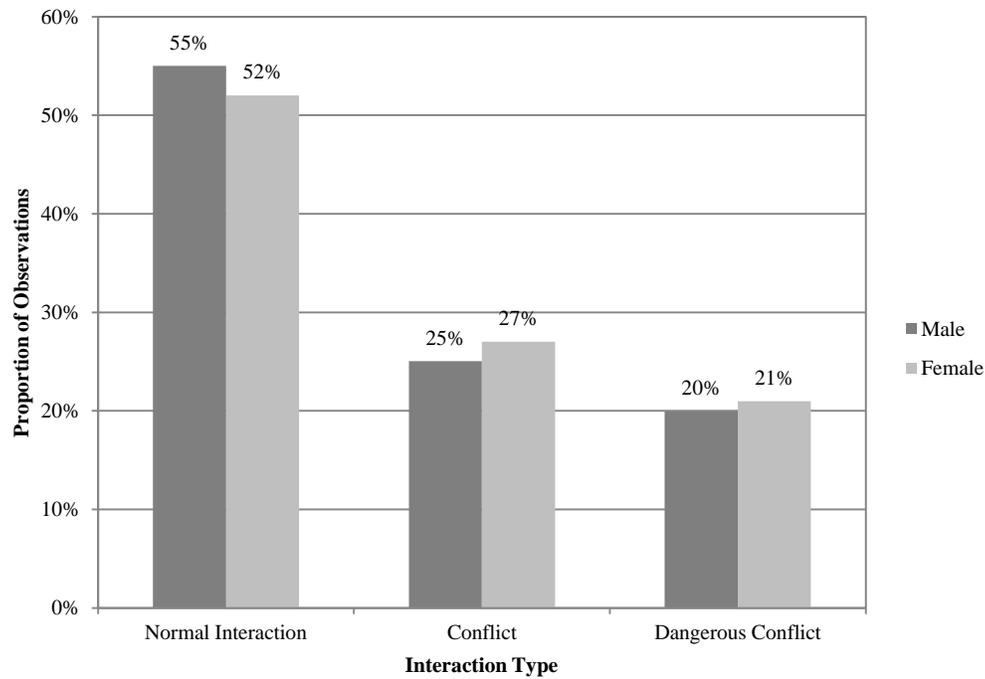
2
 3 A preliminary exploration of the raw variable data was conducted with descriptive statistics. Of the
 4 1,514 observed interactions, only 496 involved female cyclists, reflecting the disparity in number of cyclists
 5 by gender. The data set contained 33 % female cyclists, which is close to the share of 37 % female cyclists
 6 reported by Vélo Québec in 2010 (Vélo Québec, 2010). The distribution of conflicts was determined for
 7 males and females, and is presented below in FIGURE 4.
 8



9
 11
 12 **FIGURE 4 Distribution of PET for male cyclists (a) and female cyclists (b)**

13 The proportion of conflicts, dangerous conflicts, and normal interactions were determined for males
 14 and females and are provided in FIGURE 5. As the distributions seem to be drawn from the same underlying

1 distribution given the result of the chi square test at 95 % confidence (test statistic of 1.23 compared to the
 2 critical value from the chi-square distribution of 5.99), these results point towards equivalency in terms of
 3 safety for male and female cyclists. The data exploration provided little evidence of differences between
 4 genders in the considered variables.
 5



6
 7 **FIGURE 5 Proportion of Interaction Type According to Gender**

8 RESULTS

10 Model Estimation

11 The models were estimated using all available parameters and systematically eliminating statistically
 12 insignificant variables. In the results that follow, variables retained were significant at 80% confidence or
 13 greater. Variables significant at 90% confidence are italicized, and variables significant at 95% confidence
 14 are bolded. Results for the ordered logit models are presented in TABLE 2. In Model OL1, which assumed
 15 gender homogeneity, both cyclist and vehicle speed were found to be significant, along with the red light
 16 variable and several site specific constants. A log-likelihood ratio test was used to compare OL1 to the
 17 constants-only model. The null hypothesis was that none of the variables help to explain conflict severity.
 18 LR for Model OL1 was 55.72, compared to the critical value from the chi-square distribution of 14.07 (7
 19 degrees of freedom at 95% confidence). The null hypothesis was rejected, and OL1 was superior. Adding
 20 the gender variable in Model OL2 produced only minor changes in the model results. Although the male
 21 dummy variable is negative, which indicates that males have a lower propensity for conflicts than females
 22 with all else being equal, and although the gender variable was significant at 80% confidence, Model OL2
 23 was inferior to OL1 by log-likelihood ratio test (LR of 1.88 compared to a chi-square value of 3.84). Based
 24 on this result, any evidence for variation in conflict severity between males and females is inconclusive.
 25

1 **TABLE 2 Model Results for Ordered Logit Models, OL1 and OL2**

Explanatory variables	OL1			OL2		
	$y^* = \beta_1 X + \varepsilon$			$y^* = \beta_1 X + \beta_3 w + \varepsilon$		
	Parameter	z stat	p value	Parameter	z stat	p value
Bike Speed	0.0193	2.07	0.039	0.0190	2.03	0.042
Helmet	-	-	-	-	-	-
Vehicle Speed	0.0187	2.31	0.021	0.0194	2.38	0.017
Truck/Van	-	-	-	-	-	-
Platoon Leader	-	-	-	-	-	-
Red	-0.7420	-4.78	0.000	-0.7460	-4.80	0.000
Bike First	-	-	-	-	-	-
Pedestrian	-	-	-	-	-	-
Stanley	-0.3477	-2.36	0.018	-0.3590	-2.43	0.015
Peel	-	-	-	-	-	-
Mackay	-0.2505	-1.49	0.136	-0.2451	-1.46	0.145
Metcalfe	-0.2103	-1.54	0.123	-0.2123	-1.56	0.119
Denis	-	-	-	-	-	-
Union	<i>-0.4244</i>	<i>-1.80</i>	<i>0.072</i>	<i>-0.4313</i>	<i>-1.83</i>	<i>0.067</i>
Male	<i>N/A</i>	<i>N/A</i>	<i>N/A</i>	-0.1459	-1.38	0.169
Tau 1		0.5381			0.4482	
Tau 2		1.7778			1.6890	
Number of cases		1514			1514	
Log likelihood at convergence		-1494.23			-1493.29	
Log likelihood for constants- only model		-1522.09			-1522.09	
Pseudo R ²		0.0183			0.0189	

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4 Results for the SOL model are presented in TABLE 3. Non-significant β_1 coefficients indicate that
5 a parameter is not significantly correlated with conflict severity for female cyclists. Non-significant β_2
6 coefficients indicate that parameter is homogeneous across genders. This formulation eliminates
7 unnecessary variables and allows for immediate testing of differences between genders. Importantly, gender
8 was found to be highly significant in this model. The SOL model was compared to OL1 using a log-
9 likelihood ratio test. The null hypothesis was that safety is homogeneous across genders and segmentation
10 is unnecessary. LR was calculated to be 11.08, compared to the critical value from the chi-square
11 distribution of 5.99 (2 degrees of freedom at 95% confidence). The null hypothesis was falsified and
12 segmentation is justified. From the results of the OL models, gender appears to have no effect on safety.
13 However, it is not that there is no effect; it is that variation exists both in propensity and in the value of the
14 parameters. Allowing for this variation is necessary to reveal gender's true effect, representing an ideal
15 scenario for an exogenously segmented model.
16

1 **TABLE 3 Model Results for Segmented Ordered Logit Model, SOL**

Explanatory variables	β_1			β_2		
	Parameter	z stat	p value	Parameter	z stat	p value
	$y^* = \beta_1 X + \beta_2 wX + \beta_3 w + \epsilon$					
Bike Speed	-	-	-	0.0272	2.31	0.021
Helmet	-	-	-	-	-	-
Vehicle Speed	-	-	-	0.0250	2.38	0.017
Truck/Van	-	-	-	-	-	-
Platoon Leader	-	-	-	0.2395	1.63	0.104
Red	-0.7713	-4.99	0.000	-	-	-
Bike First	-	-	-	-	-	-
Pedestrian	-	-	-	-	-	-
Stanley	-0.3774	-2.56	0.010	-	-	-
Peel	-	-	-	-	-	-
Mackay	-	-	-	-0.4946	-2.41	0.016
Metcalfe	-0.2384	-1.75	0.080	-	-	-
Denis	-	-	-	-	-	-
Union	-0.8953	-2.21	0.027	0.6657	1.35	0.178
	β_3			β_3		
Male	-1.1703	-3.79	0.000	-1.1703	-3.79	0.000
Tau 1			-0.2007			
Tau 2			1.0455			
Number of cases			1514			
Log likelihood at convergence			-1488.69			
Log likelihood for constants- only model			-1522.09			
Pseudo R ²			0.0219			

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Model Interpretation

4 Interpretation of the SOL model is facilitated by calculating the true value of each coefficient for both
5 genders. For females, coefficients take the β_1 values from the model estimation. For males, the β_1 and β_2
6 parameters are summed to obtain the true value, shown in TABLE 4. Variables related to cyclist attributes
7 led to several interesting results. The primary observation is the negative, highly significant coefficient for
8 the gender variable. In general, this coefficient had the largest magnitude. This result suggests that, all else
9 being equal, when interacting with vehicles, males are less likely than females to have conflicts and
10 dangerous conflicts. This result implies that males are less likely to be involved in more severe interactions,
11 as defined by the PET intervals, and it can be concluded that male cyclists who interact with vehicles are
12 safer than female cyclists who interact with vehicles. A second important observation is that the coefficient
13 for bike speed is positive, but only for male cyclists. For females, cyclist speed has no effect on their
14 potential for conflict at the studied sites. For male cyclists, travelling at a faster speed increases the
15 propensity for conflicts and dangerous conflicts. Therefore, there is a compensating effect between gender
16 and speed. Although being male reduces the chances of conflict, cycling faster increases the chances. Males
17 travelling at high speeds (25 to 30 km/h) are no safer than females. This could indicate that males who
18 travel at faster speeds are also less risk averse, and appears to support previous behavioural research that,
19 even though male cyclists are generally safer, they are less cautious (Bernhoft & Carstensen, 2008) and
20 over-estimate their own competency (Felonneau, et al., 2013).

1 **TABLE 4 Coefficient Values for Male and Female Cyclists**

Explanatory variables	Female	Male
	β_1	$\beta_1 + \beta_2$
Bike Speed	-	0.0272
Helmet	-	-
Vehicle Speed	-	0.0250
Truck/Van	-	-
Platoon Leader	-	0.2395
Red	-0.7713	-0.7713
Bike First	-	-
Pedestrian	-	-
Stanley	-0.3774	-0.3774
Peel	-	-
Mackay	-	-0.4946
Metcalf	-0.2384	-0.2384
St Denis	-	-
Union	-0.8953	-0.2296
Male	-1.1703	-1.1703

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With regards to vehicle attributes, increasing vehicle speed increased conflict propensity, again for males only. This result is intuitive, as vehicles travelling at higher speeds have less time to take evasive action, and the interactions with road users are expected to have lower PETs. However, why conflict occurrence is independent of vehicle speeds for females is unclear. Additionally, males were more likely to engage in a conflict with the first vehicle in the platoon, although the strength of this result was relatively low. This may indicate that males tend to have a more aggressive cycling behaviour, or that the behavioural approach for managing different types of interactions is different for males and females, but a more detailed analysis would be beneficial. A data set with more observations of female cyclists may help to show the true effect of these variables and enable more significant parameters to be estimated.

The only significant environmental factors were the red light variable and several site-specific constants. Conflicts and dangerous conflicts were less likely to occur immediately after a red light phase. During the green phase, motorists may be less aware of present cyclists, and may make manoeuvres with less caution. After waiting at a red light, motorists are likely to be aware of cyclists waiting adjacent to them, and so yield to them with sufficiently safe spacing. Drivers are familiar with yielding to opposing traffic after a red light phase, and so act more cautiously. Additionally, speeds of both cyclist and vehicle are lower after a red light phase, which may also decrease the severity of conflicts. With regards to the site-specific variables, Crescent, Peel, and St Denis showed no significant variation in conflict occurrence. Both males and females had a lower propensity for conflicts at Stanley, Metcalfe, and Union (although the strength of the effect at Union varied by gender). Only males had a lower propensity for conflicts at Mackay, while for females the site was no different than the reference site at Crescent.

Sample probabilities of conflict severity were calculated for several sites, Crescent, Stanley, and Union to demonstrate the impact of the modelling results. The cases assumed cyclist and vehicle travelling at the respective mean speeds, with all other binary variables set to zero. Sample probabilities for normal interaction, conflict, and dangerous conflict were calculated for males and females and are provided in TABLE 5.

1 **TABLE 5 Sample probabilities of conflict severity for male and female cyclists**

	Crescent		Stanley		Union	
	Female	Male	Female	Male	Female	Male
P (Normal Interaction)	55%	63%	64%	71%	75%	68%
P (Conflict)	25%	22%	22%	18%	16%	20%
P (Dangerous Conflict)	20%	15%	14%	11%	9%	12%

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4 These results show that males were safer at both Crescent and Stanley, as their probability of normal
5 interaction was higher, and the probabilities of conflict and dangerous conflict were both lower. In fact,
6 males were safer in many conditions, because any variables with positive coefficients were offset by the
7 large negative coefficient on the male dummy variable. At Union, females were observed to be safer than
8 males. However, this was the only one of the seven sites where this was true. The effect of the highly
9 positive male variable can only be offset by high cyclist speeds, high vehicle speeds, or through conflicts
10 with a platoon leader. In order to achieve parity between the genders, the cyclist or vehicle speeds must be
11 increased by two standard deviations (or one standard deviation each). The results demonstrate that,
12 although there are some specific situations where females were safer than males, in general, there are many
13 more cases where males are as safe, if not safer, than female cyclists. Even if this type of cycling
14 infrastructure, with a bidirectional cycle track located to the left of other travel lanes, is rather common in
15 English speaking countries (Johnson, Newstead, Charlton, & Oxley, 2011), these kinds of interactions with
16 vehicles could seem complex to manage to less experienced cyclists, or those with little confidence on their
17 own cycling abilities, such as females (Handy, 2014). The existence of an on-road path dedicated to cyclists
18 may encourage less experienced cyclists to transfer those skills learned as drivers and thus to focus their
19 attention, when the light is green for them, on traffic coming across and forgetting to take into account the
20 vehicles traveling in the same direction as them. However, in this configuration of intersection, experience
21 as a pedestrian is more appropriate to handle the situation from the cyclist's point of view. This result that
22 female cyclists were more prone to conflicts with vehicles should be confirmed on future studies with other
23 intersection configurations. It may help to explain why fewer females choose to cycle and therefore
24 contribute to the disparity in ridership by gender. It is known that females prefer routes with less vehicular
25 interactions (Garrard, Rose, & Lo Kai, 2008), and that they feel less safe than their male counterparts
26 (Bernhoft & Carstensen, 2008). These results suggest that the higher perception of risk for female cyclists
27 is linked to a higher actual risk as well.

28 CONCLUSIONS

29 This paper proposes a methodology based on video analysis and an ordered-based modeling approach to
30 investigate the relationship between cyclist gender and conflict occurrence at urban intersections with cycle
31 tracks. The combination of video-based surrogate safety measures and ordered regression models show
32 promise for future use in conflict analysis. Even basic model formulations were able to estimate parameters
33 with significant correlation to conflict severity. Although the distribution of conflict severity showed no
34 difference between genders, the segmented model identified a distinct difference in conflict severity for
35 different genders, with males having a lower propensity of conflicts and dangerous conflicts than females,
36 all else being equal. Therefore, the segmentation technique was successful in observing variation across
37 segments of the population. Furthermore, the effect of other variables could be quantified. Interestingly for
38 males, a higher cyclist speed resulted in an increased conflict severity, while conflict severity was
39 independent of speed for females. This appears to support previous research that states that male cyclists
40 tend to be less cautious and overestimate their own competency, while female cyclists tend to underestimate
41 their cycling skills, which can have negative consequences on interaction management for both genders.
42 However, as stated above, this does not necessarily mean that males are safer overall. As Johnson, et al.
43 (2011) showed, males are more likely to run red lights. Although those that run red lights may avoid
44 conflicts, this is a dangerous behaviour that may lead to more severe, though less frequent, conflicts and

1 more severe, though less frequent, collisions. These cyclists are not present in this dataset because they are
2 not interacting with vehicles turning left (the only conflict type considered) and are instead conflicting with
3 vehicles travelling through the intersection in the transverse direction. The absence of these least risk-averse
4 males from the data set may inflate the observed differences between genders. Additional study is required
5 to determine the effect of red light compliance on cyclist safety.

6 Vehicle speed was observed to increase conflict severity for males only, and males were more likely
7 to have a severe conflict with the first vehicle in a platoon. This may indicate that males tend to have a more
8 aggressive cycling behaviour, or that the behavioural approach for managing different types of interactions
9 is different for males and females, but a more detailed analysis would be beneficial. Conflicts and dangerous
10 conflicts were less likely to occur immediately after a red light phase. Drivers are familiar with yielding to
11 opposing traffic after a red light phase, and so act more cautiously. Additionally, speeds of both cyclist and
12 vehicle are lower after a red light phase, which may also decrease the severity of conflicts.

13 While the effects of many variables could be explained, the parameters of other variables require
14 additional consideration. For example, the effect of the platoon leader variable was heterogeneous with
15 respect to gender, although this variable was statistically significant at only 80% confidence. Explanation
16 of these results requires more detailed analysis to describe behavioural differences in specific traffic
17 interactions for males and females. Further limitations of this study were related to the technique for data
18 extraction. Determining gender from video footage is a subjective exercise (Johnson, Newstead, Charlton,
19 & Oxley, 2011), although less subjective techniques are more invasive. Future work should consider
20 increasing the scope of data collection to ensure more observations of female cyclists are available for
21 analysis. More observations would allow a better estimation of the parameters, and may in fact reveal more
22 significant variables related to conflict occurrence for females. However, as current methods require manual
23 extraction of the data, this may be practically difficult. With this proof of concept established, future study
24 should incorporate additional variables, including traffic and cyclist volumes, time of day, and cyclist age.
25 Importantly, if the results obtained herein can be generalized, the relationship between gender and risk can
26 be quantified and used to explain the disparity in ridership currently observed in urban populations within
27 North America.

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REFERENCES

- 1 **REFERENCES**
- 2 Abdel-Aty, M. (2003). Analysis of driver injury severity levels at multiple locations using. *Journal of*
- 3 *Safety Research*, 34, 597-603.
- 4 Bernhoft, I. M., & Carstensen, G. (2008). Preferences and behaviour of pedestrians and cyclists by age
- 5 and gender. *Transportation Research Part F*(11), 83-95.
- 6 Bhat, C. R. (1997). An Endogenous Segmentation Mode Choice Model with an Application to Intercity
- 7 Travel. *Transportation Science*, 31(1), 34-48.
- 8 Eluru, N., Bhat, C. R., & Hensher, D. A. (2008). A mixed generalized ordered response model for
- 9 examining pedestrian. *Accident Analysis and Prevention*, 40, 1033-1054.
- 10 Felonneau, M.-L., Causse, E., Constant, A., Contrand, B., Messiah, A., & Lagarde, E. (2013). Gender
- 11 stereotypes and superior conformity of the self in a sample of cyclists. *Accident Analysis and*
- 12 *Prevention*(50), 336-340.
- 13 Garrard, J., Handy, S., & Dill, J. (2012). Women and Cycling. In *City Cycling* (pp. 211-234). Cambridge,
- 14 MA: MIT Press.
- 15 Garrard, J., Rose, G., & Lo Kai, S. (2008). Promoting transportation cycling for women: The role of
- 16 bicycle infrastructure. *Preventative Medicine*, 46(1), 55-59.
- 17 Granié, M.-A. (2011). Différences de sexe et rôle de l'internalisation des règles sur la propension des
- 18 enfants à prendre des risques à vélo. *Recherche - Transports - Sécurité*, 34-41.
- 19 Handy, S. (2014). The contribution of comfort, convenience, and liking of bicycling to the bicycling
- 20 gender gap: Evidence from Davis, California. *5th International Conference on Women's Issues in*
- 21 *Transportation*, (pp. 487-496). Paris.
- 22 Holland, C., & Hill, R. (2007). The effect of age, gender and driver status on pedestrians' intentions to
- 23 cross the road in risky situations. *Accident Analysis and Prevention*, 39(2), 224-237.
- 24 Hyden, C. (1987). *The Development of a Method for Traffic Safety Evaluation: The Swedish Traffic*
- 25 *Conflicts Technique*. PhD Thesis, Lund, Sweden.
- 26 Jackson, S., Miranda-Moreno, L. F., St-Aubin, P., & Saunier, N. (2013). Flexible, Mobile Video Camera
- 27 System and Open Source Video Analysis Software for Road Safety and Behavioral Analysis.
- 28 *Transportation Research Record: Journal of the Transportation Research Board*(2365), 90-98.
- 29 Johnson, M., Newstead, S., Charlton, J., & Oxley, J. (2011). Riding through red lights: The rate,
- 30 characteristics and risk factors of non-compliant urban commuter cyclists. *Accident Analysis and*
- 31 *Prevention*, 43(1), 323-328.
- 32 Kaplan, S., Vavatsoulas, K., & Prato, C. G. (2014). Aggravating and mitigating factors associated with
- 33 cyclist injury severity in Denmark. *Journal of Safety Research*(50), 75-82.
- 34 Klop, J. R., & Khattak, A. J. (2007). Factors Influencing Bicycle Crash Severity on Two-Lane, Undivided
- 35 Roadways in North Carolina. *Transportation Research Record: Journal of the Transportation*
- 36 *Research Board*, 1674, 78-85.
- 37 Kockelman, K. M., & Kweon, Y.-J. (2002). Driver injury severity: an application of ordered probit
- 38 models. *Accident Analysis and Prevention*, 34, 313-321.
- 39 Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: A review and
- 40 assessment of methodological alternatives. *Transportation Research Part A*, 44(5), 291-305.
- 41 Lusk, A. C., Furth, P. G., Morency, P., Miranda-Moreno, L. F., Willet, W. C., & Dennerlein, J. T. (2011).
- 42 Risk of injury for bicycling on cycle tracks versus in the street. *Injury Prevention*, 131-135.
- 43 Mannering, F. L., & Bhat, C. R. (2014). Analytic methods in accident research: Methodological frontier
- 44 and future directions. *Analytic Methods in Accident Research*, 1-22.
- 45 Martinez-Ruiz, V., Jimenez-Mejias, E., de Dios Luna-del-Castillo, J., Garcia-Martin, M., Jimenez-
- 46 Moleon, J. J., & Lardelli-Claret, P. (2014). Association of cyclists' age and sex with risk of
- 47 involvement in a crash before and after adjustment for cycling exposure. *Accident Analysis and*
- 48 *Prevention*, 62, 259-267.

- 1 Miranda-Moreno, L. (2006). *Statistical models and methods for identifying hazardous locations for safety*
2 *improvements*. PhD Thesis.
- 3 Moore, D. N., Schneider IV, W. H., Savolainen, P. T., & Farzanah, M. (2011). Mixed logit analysis of
4 bicyclist injury severity resulting from motor vehicle crashes at intersection and non-intersection
5 locations. *Accident Analysis and Prevention*, *43*, 621-630.
- 6 O'Donnell, C. J., & Connor, D. H. (1996). Predicting the severity of motor vehicle accident injuries using
7 models of ordered multiple choice. *Accident Analysis and Prevention*, *6*, 739-753.
- 8 Peesapati, L. N., Hunter, M. P., & Rodgers, M. O. (2013). Evaluation of Postencroachment Time as
9 Surrogate for Opposing Left-Turn Crashes. *Transportation Research Record: Journal of the*
10 *Transportation Research Board*(2386), 42-51.
- 11 Santamarina-Rubio, E., Perez, K., Olabarria, M., & Novoa, A. M. (2014). Gender differences in road
12 traffic injury rate using time travelled as a measure of exposure. *Accident Analysis & Prevention*,
13 *65*, 1-7.
- 14 Saunier, N. (2015). *Traffic Intelligence*. Retrieved from <https://bitbucket.org/Nicolas/trafficintelligence/>
- 15 Saunier, N., & Sayed, T. (2007). Automated Analysis of Road Safety. *Transportation Research Record:*
16 *Journal of the Transportation Research Board*(2019), 57-64.
- 17 Saunier, N., Sayed, T., & Ismail, K. (2010). Large-Scale Automated Analysis of Vehicle Interactions and
18 Collisions. *Transportation Research Record*(2147), 42-50.
- 19 Savolainen, P. T., Mannering, F. L., Lord, D., & Quddus, M. A. (2011). The statistical analysis of
20 highway crash-injury severities: A review and assessment of methodological alternatives.
21 *Accident Analysis and Prevention*, *43*(3), 1666-1676.
- 22 Sayed, T., Zaki, M. H., & Autey, J. (2013). Automated safety diagnosis of vehicle–bicycle interactions
23 using computer vision analysis. *Safety Science*, *59*, 163-172.
- 24 Strauss, J., & Miranda-Moreno, L. F. (2013). Spatial modeling of bicycle activity at signalized
25 intersections. *The Journal of Transport and Land Use*, *6*(2), 47-58.
- 26 Strauss, J., Miranda-Moreno, L. F., & Morency, P. (2014). Multimodal injury risk analysis of road users
27 at signalized and. *Accident Analysis and Prevention*, *71*, 201-209.
- 28 Tom, A., & Granié, M.-A. (2011). Gender differences in pedestrian rule compliance and visual search at
29 signalized and unsignalized crossroads. *Accident Analysis & Prevention*, *43*(5), 1794-1801.
- 30 Transport Canada. (2014). *Canadian Motor Vehicle Traffic Collision Statistics*. Retrieved December 3,
31 2014, from Transport Canada:
32 http://www.tc.gc.ca/media/documents/roadsafety/cmvtcs2012_eng.pdf
- 33 van der Horst, A. A., de Goede, M., de Hair-Buijssen, S., & Methorst, R. (2014). Traffic conflicts on
34 bicycle paths: A systematic observation of behaviour from video. *Accident Analysis and*
35 *Prevention*, *62*, 358-368.
- 36 Vélo Québec. (2010). *Bicycling in Québec in 2010*. Vélo Québec.
- 37 Wang, X., & Abdel-Aty, M. (2008). Analysis of left-turn crash injury severity by conflicting pattern using
38 partial. *Accident Analysis and Prevention*, *40*, 1674-1682.
- 39 Winters, M., Davidson, G., Kao, D., & Teschke, K. (2011). Motivators and deterrents of bicycling:
40 comparing influencers on decisions to ride. *Transportation*, *38*(1), 153-168.
- 41 Zangenehpour, S., Miranda-Moreno, L. F., & Saunier, N. (2015). Video-based automatic counting for
42 short-term bicycle data collection in a variety of environments. *Transportation Research Board*
43 *94th Annual Meeting*. Washington D.C.
- 44 Zangenehpour, S., Miranda-Moreno, L., & Saunier, N. (2013). Impact of Bicycle Boxes on Safety of
45 Cyclists: a Case Study in Montreal. *TRB Annual Meeting Compendium of Papers*. Washington,
46 DC.
- 47 Zangenehpour, S., Miranda-Moreno, L., & Saunier, N. (2014). Automated Classification in Traffic Video
48 at Intersections with Heavy Pedestrian and Bicycle Traffic. *Transportation Research Board*
49 *Compendium of Papers*.

- 1 Zangenehpour, S., Strauss, J., Miranda-Moreno, L., & Saunier, N. (2015). Are Intersections With Cycle
- 2 Tracks Safer? A Control-Case Study Based On Automated Surrogate Safety Analysis Using
- 3 Video Data. *TRB Annual Meeting Compendium of Papers*. Washington, DC.
- 4