THE WHO AND WHERE OF ROAD SAFETY: EXTRACTING SURROGATE INDICATORS FROM SMARTPHONE-COLLECTED GPS DATA IN URBAN ENVIRONMENTS

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ABSTRACT

Environment and driver behaviour are significant contributory factors in traffic collisions. Surrogate safety measures, non-crash measures that are physically and predictably related to crashes, provide opportunities for user-centric approaches to road safety and reduce dependency on crash data in environment-centric approaches. The purpose of this study is to extract surrogate safety measures from the smartphone-collected GPS data of regular drivers and to analyze those measures from an environment-centric and user-centric perspective. GPS travel data was collected using the Mon Trajet smartphone application in Quebec City, Canada over 21 days. Crash data was obtained from the Ministry of Transportation Quebec for a five year period from 2006 to 2010. The selected surrogate indicator, hard braking events (HBEs), demonstrated a spatial correlation of 0.67 with collision occurrence. Despite strong correlation, HBEs tend to overestimate risk on highway facilities and underestimate risk on local and arterial streets as the sample data collected from regular drivers likely over-represents travel on highways and under-represents travel on urban streets. The user-centric analysis showed that more HBEs occur during the AM and PM peak periods, and that braking in the PM peak period tends to be more severe, demonstrating that HBEs are not only spatially correlated with actual collision occurrence, but also make sense intuitively with respect to the behaviours related to collision occurrence. Future work will determine if other surrogate indicators that are more closely correlated with collision occurrence can be extracted, and disaggregating the analyses by facility type should improve the results.

Keywords: surrogate safety, smartphone, GPS, urban, collision prediction, behaviour, probe vehicles

INTRODUCTION

Environment and driver behaviour are significant contributory factors in traffic collisions and important influencers of road safety (*1*). Naturally, effective safety improvements should be environment-centric (addressing the '*where*' of collisions) or user-centric (addressing the '*who*' of collisions) or both. Environment-centric approaches involve identifying and remediating high-risk sites that "create an increased risk of unforeseeable accidents" due to their design or operation (*2*). Screening methods based on crash frequency or severity ranking criteria have traditionally been used to identify hazardous locations. Unfortunately, crash-based methods are reactive (*2*), require long collection periods to accumulate the necessary volume of crash data for analysis (*3*), are subject to errors and omissions in collision databases, and are sensitive to crash underreporting (*4*). These issues are particularly important in developing countries where the lack of reliable crash data inhibits implementation of crash-based techniques. User-centric approaches attempt to understand the relationship between driver behaviour and crash occurrence (*1*), often using naturalistic driving data collected unobtrusively in crashes, near crashes, and normal conditions. Naturalistic methods provide information difficult to observe by other techniques (*5*, *6*) and allow for the use of surrogate safety measures based on behaviour rather than indicators based on collision statistics. Surrogate safety measures are non-crash measures that are physically and predictably related to crashes (*7*), and provide opportunities for user-centric approaches to road safety while reducing dependency on crash data in environment-centric approaches (*8*).

Naturalistic approaches typically yield large volumes of data from which surrogate indicators must be identified (*5*). Various methods for analyzing naturalistic data have been proposed, including the use of human observers. Though human observation practically limits the amount of data that can be analyzed and measurements may be subjective (*8*), human judgement provides a level-of-detail beyond what is currently possible through objective techniques (*8*). Compared to human observation, roadside-based sensors increase the sampling rate of road users and improve objectivity. Among methods for surrogate safety analysis, the traffic conflict technique using video-based sensors and computer vision techniques has been popular for before and after studies (*2*). Though video-based sensors provide high temporal resolution (*2*) and rich positional data beyond counts and speed (*9*), the analysis of video data is potentially time and resource intensive (*2*, *8*), and interpretation of video data in behaviour terms requires additional consideration (*8*). Indicators based on traffic parameters collected by traditional point sensors including loops, radar, or other sensors (*10*, *11*, *12*) have yet to be proven as reliable surrogate safety measures, and the costs of these technologies make it impractical to implement theme across an urban network (*13*).

In-vehicle sensors provide the best opportunity for collecting spatio-temporal naturalistic driving data within a road network. Instrumented vehicles (probe vehicles or floating car data) act "as moving sensors, continuously feeding information about traffic conditions" (*14*). GPS devices are reliable sources of naturalistic driving data (*15*) and may be complemented by additional vehicle kinematics from accelerometers or gyroscopes and environmental factors collected by external sensors such as radars. These sensors provide long periods of continuous data for a small sample of road users (*2*). Though the method is limited in terms of the studied population of drivers, the spatial coverage of GPS data makes it ideal for studying environmental factors, and the naturalistic nature of GPS data makes it ideal for addressing behavioural factors (*1*). Furthermore, new technologies, including GPS-enabled smartphones, have made and will continue to make obtaining GPS data from vehicles easier over time. This leads to opportunities for real time data collection and safety analysis which is potentially interesting for emergency services.

The purpose of this study is to examine surrogate safety measures derived from probe vehicle data collected by the GPS-enabled smartphones of regular drivers. The objectives of this research are to correlate GPS-based surrogate measures to actual collision occurrence, to analyze those surrogate measures from both an environment-centric and user centric perspective, and to discuss the strengths and limitations of GPS data in surrogate safety analysis.

LITERATURE REVIEW

Though probe vehicles have been widely used in spatio-temporal applications such as traffic monitoring and origin-destination studies (*13*), applications in road safety have been less common. Automated incident

detection (AID) involves the identification of "non-recurring events such as accidents" through pattern classification of traffic flow (*16*), and improves safety by reducing secondary collisions (*17*). Existing techniques using dedicated probe vehicles have low penetration rates and are insufficient for providing "an exhaustive coverage of the transportation network" (*13*). Therefore, probe vehicles are often used in conjunction with traditional roadside sensors (*14*). In research applications, traffic simulation has been used to achieve proportions of dedicated probe vehicles beyond that which is possible in the field. Sethi et al. (*17*) found that probe vehicles improve successful incident detection rates and decreased false alarm rates over roadside sensors alone, though only when using a proportion of dedicated probe vehicles beyond what could be expected in practice (*17*). Dia and Thomas (*16*) similarly achieved the best results when probe vehicles comprised 20% of the traffic stream (*16*).

User-centric approaches using probe vehicles have been somewhat infrequent. Fazeen et al. (*19*) used smartphone accelerometer data to classify 'safe' accelerations and decelerations from 'unsafe' ones (approximately 3 m/s^2 or greater), though failed to demonstrate whether 'unsafe' behaviour led to increased collision risk. Jun, Ogle, and Guensler (*15*) analyzed the relationship between spatio-temporal driving activity and likelihood of crash involvement. Using dedicated GPS devices and self-reported safety data, the study found that drivers involved in crashes tended to travel longer distances and at higher speeds, and also "engaged in hard deceleration events" (greater than 2.7 m/s^2) more frequently (*15*). Though failing to show a causal link between decelerations and collision risk, the authors suggest that decelerations "may be employed as roadway safety surrogate measures" (*15*). Although behavioural studies typically consider differences in demographics, they frequently fail to consider temporal and spatial factors (*1*). Ellison, Greaves, and Bliemer (*1*) studied 106 drivers using GPS devices to collect speed, speed limit, location, and timestamp for every second of vehicle operation, along with demographic surveys for each driver. By controlling for temporal and spatial factors including geometry, weather, time of day, trip purpose, and vehicle occupancy, the authors found that the road environment was a significant influencer of driver behaviour (*1*). However, as 90% of all traffic collisions involve behavioural factors (*20*), this points to the strong indirect effect of road environment on safety through behavioural influence.

Probe-based surrogate safety measures aim to identify drivers avoiding collisions through evasive manoeuvres including steering, braking, or accelerating (*21*). Although speed is often regarded as an important surrogate measure, changes in speed (acceleration or jerk) may be more important (*8*). Algerholm and Larhmann (*2*) used data collected from 6 drivers over a 3 month period using GPS devices and accelerometers. The authors stated that "braking was the evasive action […] in 88% of the accidents in built-up areas" (*2*), making decelerations a logical indicator to extract. Jerk was found to be correlated with accident occurrence both across drivers (user-centric) and across sites (environment-centric) (*2*). Bagdadi (*5*) noted that the most common crashes are rear-end collisions, and used GPS, accelerometer, and radar data from 109 participants. The proposed surrogate measure based on jerk was used to correctly identify self-reported near misses at an 86% success rate (*5*). One shortcoming of this study is that the ground truth data used was itself a surrogate measure (near misses) and not actual collision data.

Several shortcomings are apparent in the existing literature, which this study attempts to address. First, there has been no attempt to derive surrogate safety measures from smartphone-collected GPS data of regular drivers alone. Existing studies have used dedicated probe vehicles (resulting in sample sizes of 100 drivers or less) or dedicated GPS devices with supplemental accelerometer data. Second, there has been no comprehensive comparison of GPS-based surrogate indicators to large quantities of crash data. Instead, studies have compared indicators to sample safety data, which is often self-reported. Thirdly, there has been little effort to consider user-centric and environment-centric approaches simultaneously.

METHODOLOGY

Data Collection

Naturalistic driving data should be collected as unobtrusively as possible, to ensure data accurately represents normal driving conditions. Collecting GPS data from smartphones allows for the study of regular drivers using a system that minimally impacts their behaviour, and the implementation of a smartphone

application makes use of devices already widely available to the driving population reducing cost and increasing potential sample size. Smartphone applications, such as Mon Trajet (*22*, *23*) by Brisk Synergies (*24*), shown in FIGURE 1, are installed voluntarily by drivers and collect GPS data anonymously. General trip information, including route, origin and destination, and start and end time, are captured for every user-reported trip logged in the application. Travel is described by observations including user speed, latitude, longitude, and altitude captured for every 1-2 seconds of vehicle operation. Other socio-demographic information may also be available depending on the configuration of the application. Once a trip has been collected and reported by the user, initial pre-processing of the data is completed using Kalman filtering to reduce data variability. The GPS data is then stored in remote databases, from which the raw GPS observations are exported for further analysis.

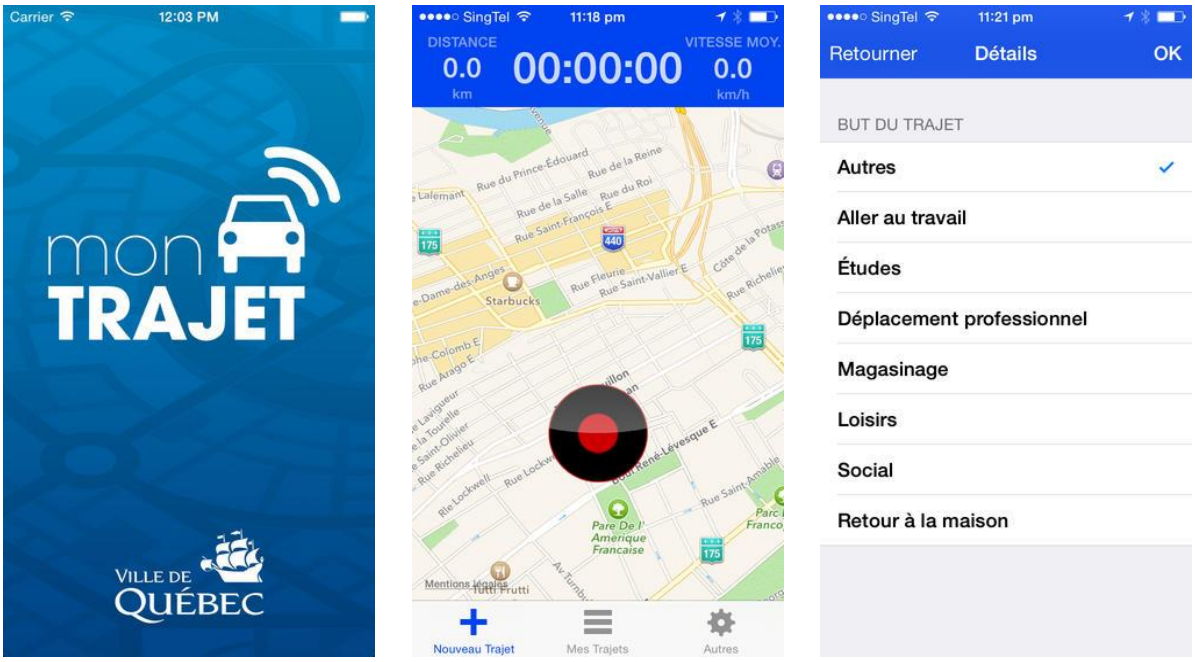


FIGURE 1 Smartphone application interfaces

Data Cleaning

Although GPS data from a smartphone application is rich in spatio-temporal data, raw GPS traces contain variability in both position and speed. Even with pre-processing of the user data, additional data cleaning methods are required. Although Kalman filtering is popular, the method only smooths vehicle positions in terms of a latitude and longitude and does not explicitly link trips to the road network. This study used a map-matching process to ensure that trips are correctly matched to the links in the road network where they occurred. Vehicle speed measurements were cleaned using exponential smoothing.

Map Matching

TrackMatching is a commercially available, cloud-based web map-matching software service (*25*) that matches GPS data trip data to the OpenStreetMap (OSM) road network (*26*). Before GPS data is sent to TrackMatching, the data must be split into individual trips and formatted according to the input requirements of the software, including only the coordinate id, timestamp, latitude, and longitude for each observation. The software returns a map-matched OSM ID (link ID), map-matched latitude and longitude, and source and destination nodes along the OSM link for each GPS observation. Importantly, because much important information (user ID, speed, timestamp, etc.) is lost through the map matching process, the results must be merged back with the original data to preserve the complete data set.

Speed Smoothing

Simple exponential smoothing is used to eliminate noise and outliers within the GPS-collected speed data by generating new speed estimates for each observation (*27*). The smoothing equation is given by

$$\hat{Y}_t = \alpha Y_t + (1 - \alpha)\hat{Y}_{t-1} \quad (1)$$

where $\hat{Y}_t$ is the estimated speed at the current time step, t; Y_t is the speed at the current time step as measured by the GPS, t; $\hat{Y}_{t-1}$ is the estimated speed at the previous time step, $t-1$; and α is the smoothing parameter. Increasing alpha increases the effect of the observed speed (less smoothing) while decreasing alpha increases the effect of the last estimated speed (more smoothing). If alpha is too large, then smoothing is minimal, and noise in the GPS data may be wrongly interpreted as braking (type II error). If alpha is too small, then smoothing can potentially eliminate actual braking events (type I error). Smoothing parameters of 0.4, 0.6, and 0.8 were tested. The process of collecting and cleaning the GPS data is illustrated in FIGURE 2.

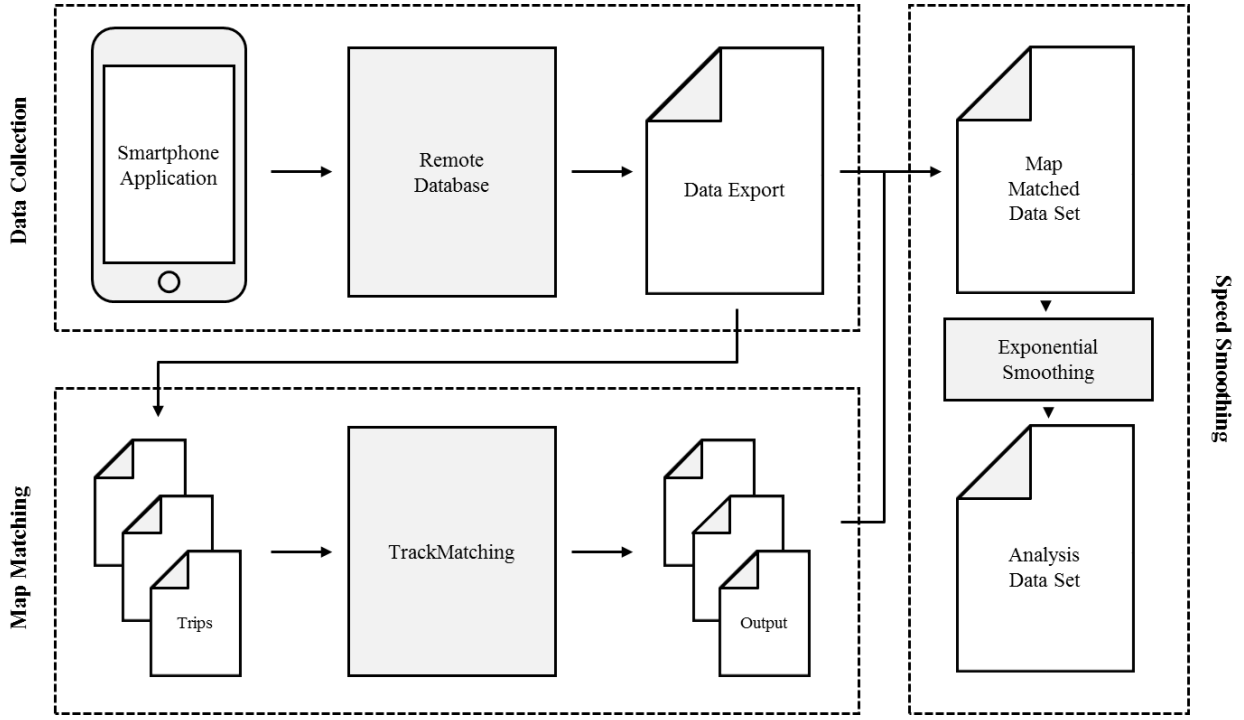


FIGURE 2 Collection and cleaning of smartphone-collected GPS data

Extraction of Surrogate Indicators

After the data has been collected and cleaned, the surrogate safety measures are extracted from the analysis data set. Recognizing that deceleration is perhaps the most common evasive manoeuvre in urban areas (*2*), selecting hard braking events (HBEs) as the surrogate indicator of interest is logical. Studies focussed on deceleration have used jerk, observed using accelerometers, to define the surrogate indicator (*2*, *5*). When using GPS data alone, calculating jerk-based surrogate safety measures is not possible, as GPS observations are too infrequent to capture the required detail. However, Fazeen et al. (*19*) suggested that decelerations exceeding 3 m/s^2 were an indicator of 'unsafe' behaviour. Therefore, using a deceleration threshold may be sufficient to define HBEs. Although the 3 m/s^2 threshold is a starting point to develop GPS-based surrogate indicators, thresholds of 4 m/s^2 and 5 m/s^2 were also tested. An algorithm was developed to automatically identify all instances where a vehicle exceeded the threshold. HBEs were then analyzed from both environment-centric and user-centric perspectives.

Environment-Centric Analysis

Spearman Rank Correlation

As surrogate safety measures must be predictably related to crashes (*7*), any proposed measure must demonstrate correlation with actual safety or risk. Spearman's Rank Correlation Coefficient, or Spearman's rho, indicates how strongly the dependency between two variables is described by a monotonic function and is a popular choice for correlating surrogate indicators with crash data. Locations with the most collisions should also have the most HBEs, and sites with fewer collisions should have fewer HBEs. A rho of 1.0 indicates positive correlation, 0.0 indicates no correlation, and -1.0 indicates negative correlation. Spearman's rho, ρ, is calculated using

$$\rho = 1 - \frac{6\sum(x_i - y_i)^2}{n(n^2 - 1)} \quad (2)$$

where x_i and y_i are the ranks of site i in the two data sets and n is the total number of sites. The ranks, x_i and y_i, were created by generating buffers around each intersection (any point where two OSM links meet or intersect) in the road network using GIS. The total numbers of collisions and HBEs within the buffers were then counted, and intersections were ranked based on these counts. The effect of buffer size on correlation was determined by comparing results generated with 100 m, 200 m, and 500 m buffers.

Hot Spot Analysis

Although Spearman's rho generally quantifies the correlation between a surrogate safety measure and collision occurrence, additional analysis is necessary to observe discrepancies between the data sets. Heat maps generated using GIS can be compared visually to determine where the surrogate measure performs well (has strong agreement with the crash data) and where performance is poor. Heat maps were generated in GIS for both collisions and HBEs using a 500 m radius and 50 m pixel width.

User-Centric Analysis

Rather than just considering the locations in the road network where hard braking events occur, a user-centric approach to surrogate safety can show which characteristics or behaviours of drivers contribute to the occurrence or severity of HBEs and therefore collisions (if the link between HBEs and collisions is demonstrated). Though driver socio-demographics were not collected, consideration for spatio-temporal driving behaviour (*15*) is possible based on GPS data. The user-centric analysis was completed using two ordered logit models. The first model was used to analyze the occurrence of hard braking events. In this model, trips were divided into trips with at least one HBE above 3 m/s^2 (Alternative 1), and trips with none (Alternative 0). The dependent variables included trip characteristics of length and average speed, and time-of-day characteristics indicating whether the trip occurred during the AM peak period (6:00 AM to 9:00 AM), PM peak period (4:00 PM to 7:00 PM) or at night (10:00 PM to 4:00 AM), and whether the trip was made on a weekday or on the weekend.

A second ordered logit model was used to analyze the severity of braking events. In this model, trips without HBEs above 3 m/s^2 were ignored. The remaining trips were grouped according to the hardest braking event experienced during the trip; Alternative 0, 3-4 m/s^2; Alternative 1, 4-5 m/s^2; and Alternative 2, 5 m/s^2 or greater. The same dependent variables were considered with the addition of instantaneous vehicle speed immediately before the HBE occurred.

DATA DESCRIPTION

This study made use of three primary data sources. GPS travel data was collected in Quebec City, Canada using the Mon Trajet application by Brisk Synergies (*24*). In total, approximately 5000 driver participants have logged nearly 50,000 trips using the application. However, the sample for this study contained 2413 drivers and 12,724 individual trips during the period between April 28 and May 18, 2014. Over the 21 days

sampled, 19.7 million individual data points were logged, with observations available every 1-2 seconds during a trip. Crash data was obtained from the Ministry of Transportation Quebec for a five year period from 2006 to 2010. 9248 collisions identified across the 5-year period involved at least one vehicle. Map data used for the environment-centric analysis was obtained from OpenStreetMaps in order to maintain consistency with the map matching results.

RESULTS

Extraction of Surrogate Indicators

TABLE 1 provides the number of HBEs identified for each combination of deceleration threshold and smoothing parameter. Both of these variables were observed to greatly influence the total number of HBEs that were identified. In the most restrictive case, only 1444 events were extracted, while the least restrictive case found nearly 80,000 events.

TABLE 1 Number of Hard Braking Events Identified

		Alpha		
		0.8	**0.6**	**0.4**
Threshold	**3 m/s^2**	78457	43119	13870
	4 m/s^2	21744	9356	2719
	5 m/s^2	6958	3021	1444

Environment-Centric Analysis

Spearman Rank Correlation

Spearman's rho was calculated for three different deceleration thresholds, with three different smoothing parameters, and three different buffer sizes, for a total of 27 tests. The results are presented in TABLE 2. Smoothing parameters of 0.6 and 0.8 were found to provide roughly equivalent results, only differing by a few percentage points. An alpha value of 0.4 was inferior in all test cases (as were alpha values less than 0.4). Although a higher alpha value results in improved correlation, reducing the alpha value significantly reduces the number of events identified (as shown in TABLE 1), with only a minor reduction in correlation strength. In this case, an alpha value of 0.6 provides good correlation with far fewer observations than an alpha of 0.8. All cases with 100 m buffers failed to provide correlation above 0.50. A 200 m buffer performed better, with correlations between 0.50 and 0.60, and the 500 m provided the best results, with correlations between 0.60 and 0.70. A deceleration of threshold of 3 m/s^2 consistently provided the highest correlation, up to 0.669. For these reasons, the remainder of this paper focusses on a threshold of 3 m/s^2, alpha of 0.6, and a buffer size of 500 m (rho = 0.644).

Hot Spot Analysis

Despite relatively high correlation results, Spearman's rho provides no indication of where correlation is good and where it is poor. In order to identify differences in the data sets, hot spots were identified for both collisions, in FIGURE 4a, and HBEs, in FIGURE 4b. Visually, these maps reveal a critical difference between the crash data and the surrogate safety measures. The locations with the most collisions tend to be local streets, such as in downtown Quebec City, or on urban arterials like Laurier Boulevard and 1st Avenue. In contrast, the locations with the most HBEs tend to be on highways, such as Félix-Leclerc, Henry IV, and Charest. This is perhaps logical, as a deceleration of 3 m/s^2 is more likely when a driver is traveling at highway speeds compared to urban arterials and local streets. This is a crucial discrepancy, as priority sites identified through network screening would be very different if using HBEs rather than collision data.

TABLE 2 Spearman Rank Correlation Coefficients

		Buffer Size		
		100 m	200 m	500 m
Alpha = 0.8				
Threshold	**3 m/s²**	0.497	0.564	0.669
	4 m/s²	0.453	0.522	0.639
	5 m/s²	0.386	0.474	0.610
Alpha = 0.6				
Threshold	**3 m/s²**	0.477	0.540	0.644
	4 m/s²	0.399	0.479	0.603
	5 m/s²	0.278	0.360	0.543
Alpha = 0.4				
Threshold	**3 m/s²**	0.408	0.465	0.580
	4 m/s²	0.244	0.321	0.500
	5 m/s²	0.129	0.171	0.341

Considering a correlation exceeding 0.644 was observed despite the disparity in the locations of the hot spots, it was believed that disaggregating facility types may improve the results. Consider the plot of collisions and HBEs provided in FIGURE 3. Locations with many more HBEs than collisions are likely to be highways (those that appear as hotspots in FIGURE 4b), while locations with more collisions are likely to be local or arterial streets (those that appear as hotspots in FIGURE 4a).

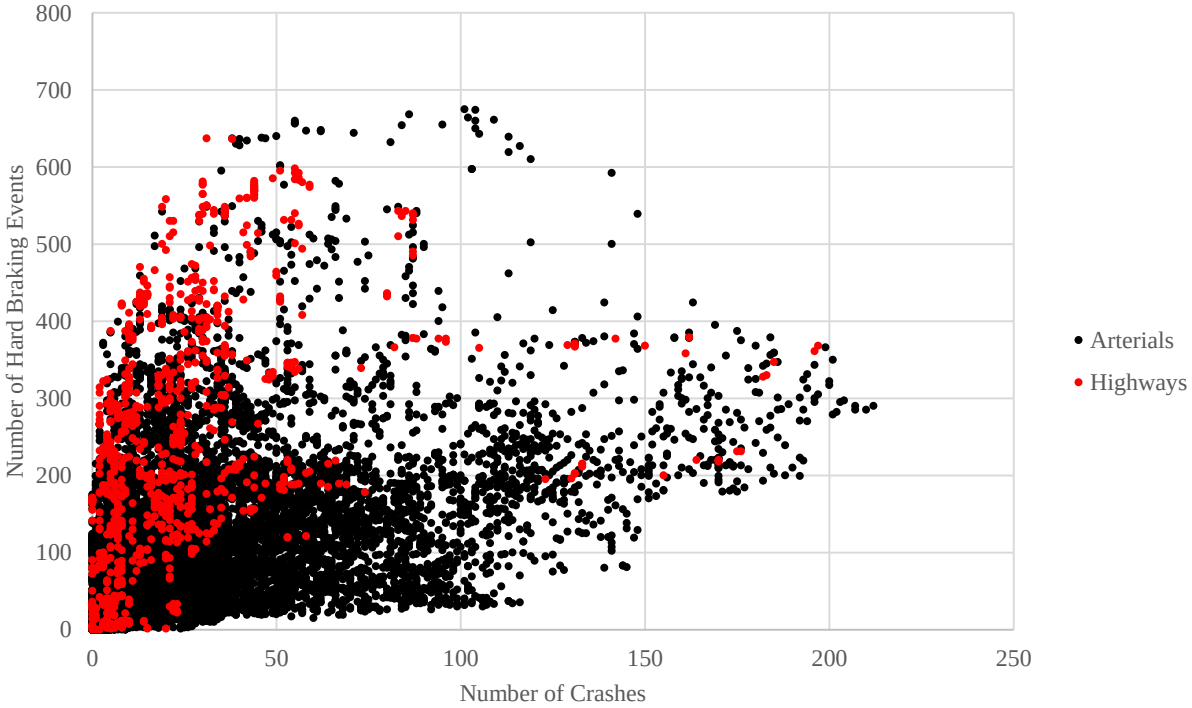
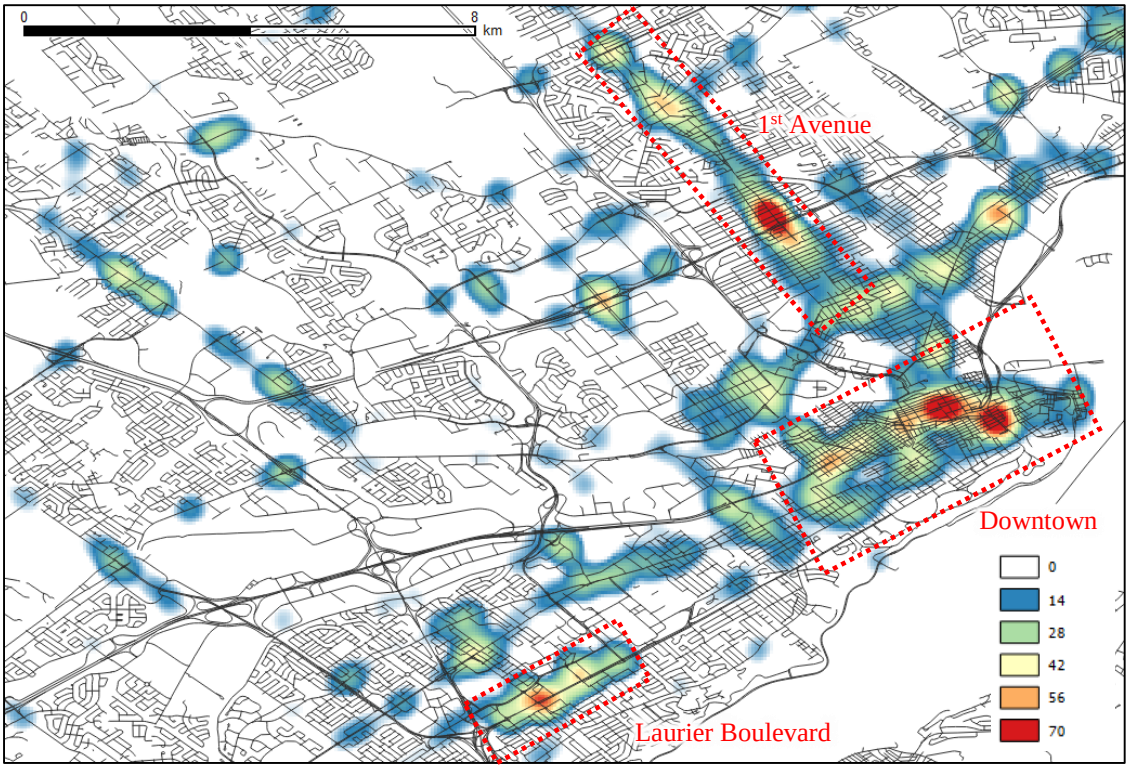
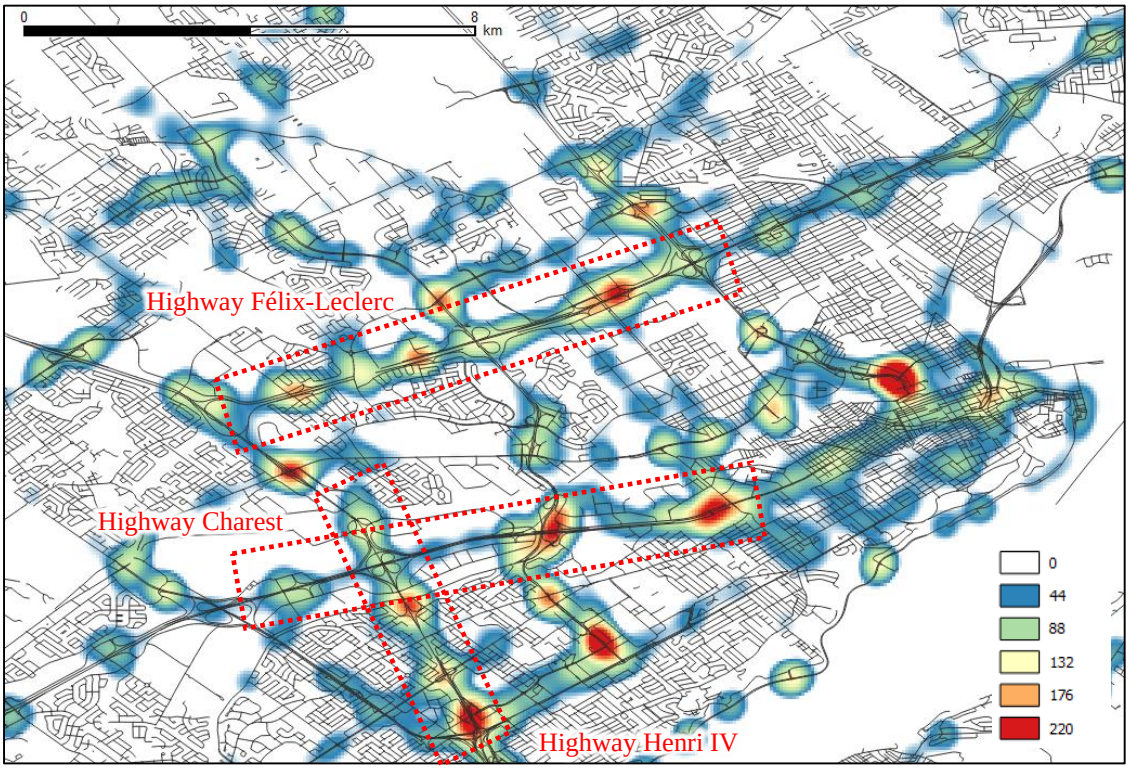


FIGURE 3 Correlation between number of hard braking events and crashes



(a)



(b)

FIGURE 4 Hot spot analysis by collision data (a) and hard braking events (b)

Comparing the lists of intersections ranked by collision occurrence and HBEs, the top 1 % identified using crash data shared no common sites with the and the top 1 % identified using HBEs. The top 5 % in both lists contained only 64 intersections in common out of 778 total (8 % similarity), and the top 25 % in both lists contained 999 intersections in common out of 3889 total (26 % similarity). With the results presented above and the apparent bimodal nature of the surrogate/crash relationship, a final attempt to improve the correlation results was made by separating highways from the local and arterial streets, and performing a separate correlation for each facility group. Intersections, collisions, and HBEs were filtered according to those corresponding to highways or highway ramps, and those occurring on all other facilities. TABLE 3 shows the new rho values based on facility type. Although the correlation for highways was lower than for all facility types combined, the correlation on local and arterial streets was improved, and an average weighted on proportion of facility type demonstrated an overall increase in correlation. However, as the total improvement in correlation was only two percentage points, this result demonstrates that although the relationship between HBEs and collision occurrence is dependent on facility type, more facility types must be considered if substantial improvements are to be made.

TABLE 3 Spearman Rank Correlation Coefficient for Highways and Local/Arterials

	Roadway Type			
	All	**Local/Arterial**	**Highway**	**Weighted**
ρ	0.644	0.674	0.536	0.664

User-Centric Analysis

The results for the braking occurrence model (which included all trips) and the braking severity model (which included only those trips with at least on HBE exceeding 3 m/s^2) are presented in TABLE 4. The model results contain only parameters significant at 95% confidence unless otherwise noted.

TABLE 4 Model Results for Occurrence and Severity of Hard Braking Events

	Braking Occurrence		Braking Severity	
Explanatory variables	**Parameter**	**z stat**	**Parameter**	**z stat**
Instantaneous Speed	N/A	N/A	0.0847	22.9
Trip Speed	*-0.0046**	*-1.52**	-	-
Trip Length	-	-	-	-
AM Peak	0.0996	2.71	-	-
PM Peak	0.1655	4.19	0.0956	2.48
Night	-	-	-	-
Weekday	-	-	-	-
Tau 1	-0.2947		1.4784	
Tau 2	N/A		3.0387	
Number of cases	20840		12087	
Log likelihood at convergence	-14167.40		-11090.47	
Log likelihood for constants-only model	-14177.35		-11356.39	

**note: coefficient for trip speed is significant at 87% confidence*

In the braking occurrence model, only the AM and PM peak period variables were found to be statistically significant. This indicates that HBEs are more common during peak periods then during other periods in the day. This result is expected as the congestion experienced in these times should contribute to increased braking and, therefore, to increased collisions. Trip length was found to have no effect on braking occurrence, while average trip speed had a negative effect, though it was only significant at 87% confidence. Other time-of-day variables also failed to show a significant relationship with braking occurrence. In the braking severity model, the PM peak period variable was again found to be significant and positive. This indicates that not only do more HBEs occur in the PM peak period, but that they tend to be more severe (harder braking) than at other times of the day. Additionally, the instantaneous vehicle speed was found to be positive and significant. Faster vehicles who use braking as an evasive manoeuver tend to brake more aggressively or severely (i.e. have a higher deceleration rate). This result is again intuitive, as it is expected that travel at higher speeds would require more severe evasive actions, and potentially more severe collisions.

CONCLUSIONS

The purpose of this study was to extract surrogate safety measures from the smartphone-collected GPS-data of regular drivers and to analyze those measures from both an environment-centric and user-centric perspective. The smoothing parameter and deceleration threshold have a strong influence the number of HBEs identified. However, buffer size has a much greater influence on the strength of the correlation to actual collision occurrence. Selecting these three parameters is a crucial step in the presented analysis. The strongest correlation between HBEs and collisions was 0.669 (threshold = 3 m/s^2, alpha = 0.8, buffer = 500 m) though reducing alpha to 0.6 only decreased correlation to 0.644 with far fewer observations. This is a promising result in this early research, as even the most aggregate approach to using HBEs as surrogate safety measures demonstrated a relatively high correlation.

Despite strong correlation, hot spots identified by both methods vary greatly. HBEs tend to overestimate risk on highway facilities and underestimate risk on local and arterial. There are several potential explanations for the disagreement. First, regardless of the sample drivers used, it is more likely that their trips will utilize highway facilities, while the probability of trips in residential neighbourhoods is low (except for the neighbourhoods were sample drivers live). Therefore, the sample of smartphone GPS data collected from regular drivers likely over-represents travel (and therefore collision risk) on highways and underrepresents travel (and risk) on urban residential streets. Disaggregating analysis by facility type showed potential for improvement, although the analysis must consider more than two facility types if improvements are to be substantial. Therefore, facility types should be disaggregated before analyses begins. Second, the use of a constant deceleration threshold is likely biased towards facilities with higher mean travel speeds. A deceleration rate of 3 m/s^2 is more probable when traveling at highway speeds compared to urban arterials and local streets. A lower deceleration rate of 2 m/s^2 may be common on highways but accurately represents evasive manoeuvers on local streets. If facility types are disaggregated, then the deceleration threshold could be set according to each specific facility type. Thirdly, hard decelerations may not be the primary evasive manoeuvre in the local and arterial streets. Other surrogate indicators should be used to capture more evasive manoeuvers in urban environments.

The user-centric analysis showed that more HBEs occur during the AM and PM peak periods, and that braking in PM peak period tends to be more severe. This result is logical as more congestion in these periods should yield more braking and more collisions. However, more congestion may also lead to reduced speed and therefore less severe collisions. This potential contradiction should be explored in future work. As vehicle speed increases, the severity of braking also increases. Intuitively, faster vehicles must decelerate more rapidly to avoid collisions. Although other spatio-temporal driving behaviours could not be linked to occurrence of braking events, the limited observations demonstrate that surrogate measures defined using braking as the primary evasive manoeuvre are not only spatially correlated with actual collision occurrence, but also make sense intuitively with respect to the behaviours that are related to collision occurrence and severity (traveling at peak periods and at higher speeds).

Limitations of this study include the use of density-based measures (heat maps). Future work should focus directly on links and/or intersections as the unit of analysis. The lack of supplemental data from accelerometers may be perceived as a limitation, though using only GPS data may be a strength of this approach, as it results in much less data that requires processing and collecting only GPS data from smartphones limits the battery requirements of the application. Additionally, correlations between HBEs and collisions was high even without this additional data. In the future, more work is needed to determine if surrogate indicators, such as over speeding or speed variation, more closely correlated with collision occurrence can be extracted from the GPS data. Additionally, further disaggregating the analyses by facility type should improve the results. Correlation at the link-level should be considered in addition to the intersection-level analysis presented above. In order to increase correlation with collision data (to use for network screening purposes), analysis could be done according to facility type (highway, primary, secondary, tertiary, local, etc.), and the threshold, smoothing parameter, and buffer size could be adjusted for each. Regardless of future improvements, hard braking events derived from the smartphone-collected GPS data of regular drivers show promising potential in the field of surrogate safety.

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