An Analysis of Vehicular Telematics and Geo-Location Data to Maximize Road Safety

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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An Analysis of Vehicular Telematics and Geo-Location Data to Maximize Road Safety *

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***Abstract*—In scores of vehicle fleets, telematic tracking systems provide fleet managers with information regarding energy consumption, compliance with safety regulations, and driver performance. For a University's Facilities Management (FM) Fleet to take the next step towards an elevated Sustainable Fleet accreditation and overall team performance, the management has recognized the importance of safety tracking methods combined with data analytics and a comprehensive systems analysis to aid the reinforcement training and maintenance of safe and sustainable driving practices by fleet drivers. This paper demonstrated an effective method of identifying safety hotspots by analyzing safety surrogate measures, such as harsh braking, harsh cornering and speeding from vehicular telematics data and combining them with their geo-location information to enhance the safety of the University of Virginia's facilities management vehicles and common drivers in the area. Instances of safety surrogate measure violations were first mapped onto a cluster map and were then normalized and combined to pinpoint which spots on campus were most prone to accidents. We then validated the cluster maps with crash data from both Facilities Management vehicles and the state of Virginia to identify safety hotspots. From the investigations, we considered a list of comprehensive safety countermeasures to address the safety infractions identified at each hot spot. These safety countermeasures were recommended based on their likelihood of reducing safety violations.**

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I. Introduction

In the realm of fleet management, the integration of telematic tracking systems has become pivotal in enhancing operational efficiency, ensuring compliance with regulations, and promoting safety among fleets. Telematics offers fleet managers data pertaining to energy consumption, adherence to safety protocols, and driver performance, which helps to facilitate informed decision-making [1]. At the University of Virginia (UVA), the Facilities Management (FM) Fleet Team oversees over 280 vehicles, striving to maintain a fleet that is both safe and efficient, thus enabling staff to fulfill their responsibilities effectively [2].

Currently, UVA FM is dedicated to serving as a leader in safety and sustainability in alignment with UVA's 2030 Sustainability Plan [3]. With safety as a paramount concern due to UVA's sprawling campus and substantial presence of drivers, the objective of this research is to identify and validate safety hotspots based on FM fleets' telematics and geolocation data and recommend countermeasures aimed at improving the safety at these hotspots. Currently, crash data are scarce within the university campus, which accentuates the significance of identifying safety hotspots. Through these efforts, we aim not only to reduce the frequency of crashes but also to cultivate a culture of safe driving practices among all road users. Ultimately, these initiatives align with the university's commitment to fostering a secure and conducive environment for learning, working, and living.

This paper proceeds as follows: The second section outlines the background of this study, which succeeds previous studies. Subsequent sections present a literature review, our analytic methods, the results, a discussion of the results, a conclusion, and suggestions for future research.

II. Background

From 2019-2024, FM had a total of 114 reported crashes. Over the course of two years, FM has partnered with the UVA Systems Engineering Research team to improve safety and sustainability to support UVA's 2030 Sustainability Plan [3]. While past research has been performed on mindful driving and training, FM determined the importance of minimizing these crashes to attain its goal of safety and sustainability among its fleet. Similarly to this paper, these past studies utilized telematics data from GeoTab, a third-party data monitoring platform used by FM.

In 2021, a research team developed an agency-specific mindful driving program to reduce compliance and fuel consumption-related fleet incidents. Safety measures, including harsh braking and speeding, were like those in this paper. The study compared metrics before and after training implementation on drivers with poor habits, but the short timeframe limited meaningful analysis [4]. In 2022, the team proposed two reinforcement training courses, reactive and proactive, using in-vehicle sensor data to reinforce safe driving lessons. Results showed a significant decrease in speeding with reactive training [5]. Last year, in 2023, a new research team aimed to quantify safety and mobility benefits from mindful driving training, intending to incorporate it into a new employee's orientation. Findings suggested long-term benefits for the fleet vehicles, including reduced safety violations and fuel costs [6].

III. Literature Review

This section discusses geofencing, crash surrogates, and countermeasures, which are relevant to identifying safety hotpots using vehicular telematics data.

A. *Geofencing*

Identifying vehicle safety violations in extensive datasets is complex due to overlapping data points. Previous studies have employed geofencing to efficiently identify and compare hotspots. Desai and his research team demonstrated this in their study correlating harsh braking events and crash occurrences at Interstate Highway construction sites in Indiana. They used geofences to delineate crash-prone work zones, enabling size and distance-independent comparisons [7]. Shen and his research team also utilized geofencing, using 500ft by 500ft section of roadways as areas of analysis to predict motor vehicle crash occurrences based on aggregated fine geo-resolution vehicle telematics data. Their study compared geo-sports using a normalized metric of acceleration, braking, and cornering events, identifying high-risk areas [8]. Both studies highlight the benefits and feasibility of geofencing for comparing potential crash hotspots. In contrast, this research extends geofencing to smaller, mainly one-lane roads.

B. *Crash Surrogate Measures*

In prior research, surrogate measures for car crashes have been used using different thresholds and metrics due to the inadequacy in motor crash data [9]. Traffic conflicts have historically served as a comprehensive surrogate measure for crashes, defined as events involving road users necessitating evasive maneuvers to avoid collisions [10]. However, measuring traffic conflicts relies on observational data, posing challenges for data generation. Vehicular telematics data, particularly harsh acceleration, braking, and cornering has been utilized to predict crashes [8]. Zhang and her team identified crash hotspots in Ann Arbor, Michigan, using sudden braking events on freeways [11], while Desai found a correlation between harsh braking with crash occurrences on interstate construction projects [7]. Both studies found a significant correlation between harsh braking and crashes. Gupta and his team affirmed this connection but found cornering to be less indicative. These surrogate measures offer promise in pinpointing safety hotspots, including those around the University of Virginia [12].

C. *Countermeasures*

Countermeasures are essential for enhancing safety in identified hotspots, especially considering the University of Virginia's predominantly low-posted speed limit roads with numerous crosswalks. Previous research categorized effective countermeasures into four groups: speed management, temporal and spatial separation of pedestrians and vehicles, and improving pedestrian visibility. These four defined groups of countermeasures can be obtained through the addition of traffic signs, speed bumps, pedestrian crossing, visibility of traffic signs, and the narrowing of roads [1]. Chen et al. in 2012, evaluated the effectiveness of these countermeasures in New York City, observing reductions in crash rates following implementation. Significant crash rate reductions were noted with measures such as pedestrian fencing, increased visibility of signs, extension of crossing times, and traffic signal installation [13].

Based on the literature review, we combined geofencing techniques and surrogate safety measures to identify safety hotspots and place countermeasures to improve safety at the University of Virginia campus.

IV. Methods

To determine the hotspots for safety, an empirical analysis with five steps was performed: gathering and cleaning of surrogate measure and crash data, mapping of the events' geolocations, correlation analysis of three surrogate measures and crash data, ranking of the hotspots using Z-scores, and qualitative validation of derived hotspots using state accident data. Subsequent subsections explain each step-in depth.

A. *Baseline Vehicle Data Collection and Analysis*

GeoTab is an onboard device installed on each of the 280 plus facilities management (FM) vehicles and reports various vehicular statuses, including harsh braking, speeding, hard acceleration, harsh cornering. Every surrogate measure event that is violated by an FM vehicle is recorded onto the Geotab platform. Upon analysis and deep consideration based on our literature review, our team decided to focus on harsh braking, harsh cornering, and speeding as surrogate measures that contribute to crashes. Therefore, from the Geotab platform, we pulled all instances of harsh braking, harsh cornering, and speeding by FM vehicles from the years 2019-2024 and put them into respective datasets for each measure. Harsh braking takes place when a driver neglects proper following distance or is inattentive to current environmental conditions like the presence of pedestrians. Harsh cornering occurs when a vehicle turns sharply or abruptly. Speeding occurs when a vehicle is traveling at a speed of 5 mph greater than the posted speed limit. For this study, an event for each metric for different types of vehicles was specified when exceeding the thresholds, as defined in Geotab and seen in Table I.

TABLE I. Threshold For Each Event For Types of Vehicles

Metric	Threshold Definition		
	Passenger Car	Truck/Cube Van	Heavy-Duty
Harsh Braking	-0.59 G	-0.54 G	-0.47 G
Hard Cornering	0.47 G	0.4 G	0.32 G
Speeding	> 5 mph posted speed limit		

Each violation event provided us with data on the time, date, latitude, and longitude, and the speed the vehicles were going. However, we realized that we had to do some data cleaning. There were harsh braking and harsh cornering events that had speeds of zero or speeds that were not fast enough to exceed each respective threshold (from zero to five mph). Many of these events were caused by dangling events, caused when the Geotab device is not installed correctly onto the vehicle. This was confirmed through testing where we manually hit the device. Dangling events also occur during the testing phase of the device, as many events were seen to occur in FM headquarters or testing centers. To address these instances, we queried the data to only include events that occurred above five miles per hour speed. We chose this speed because it is the lowest speed limit within the campus of UVA, so it would theoretically be the lowest speed a car drives around the school.

To cross-reference the surrogate measure map to determine the safety hotspots on campus, we needed to find data on the crashes in Charlottesville. We incorporated crash data from the Facilities Management fleet vehicles from 2019 to 2024. On top of this, we pulled data from the Traffic Roads Electric Data in Virginia (TREDS) [14], which contained its own cluster map of all crashes in the Charlottesville area. In the TREDS Virginia data, there were datasets for both Albemarle County, where Charlottesville is, and for Charlottesville City itself from 2019 to 2024. Since there were no overlaps between crashes in both data sets, they were both used.

B. *Mapping Safety Surrogate Measure Violations*

Using the provided latitude and longitude coordinates for each surrogate measure event and FM vehicle crashes, we were able to generate maps showing each event using Python and C# programs. We first created a Python file that queried surrogate measure data from each FM vehicle from GeoTab and stored all instances from each vehicle into their own log files. From there, we had a C# file that traversed each log file to map all instances into a cluster map. This provided the initial information needed to identify safety hotspots. These cluster maps were implemented to ensure accurate hotspot identification and group events together based on proximity to an area. Colors were incorporated into the cluster map to identify key areas of each cluster. The greater the proportion of events in relation to other clusters, the redder the cluster appears. Green clusters denote low event areas, while yellow clusters denote medium event areas, and red clusters denote high event areas, as seen in Figure 1. As the clusters expand, areas with a greater density of events are more easily identifiable. The data on FM crashes were also transformed into a cluster map the same way the surrogate measures were.

Figure 1. Cluster Map of Harsh Cornering Events from 2019 to 2024

C. *Identifying Hotspots on Campus*

After obtaining the cluster maps, we identified the hotspots at UVA. We did this by first dividing UVA into twenty different cluster zones based on roadway segments, as seen in Figure 2. To determine these zones, we evaluated trends from the cluster maps, looking at popular forming clusters, marking each as a potential hotspot. From there, we viewed routes from FM vehicles on GeoTab to determine which segments are commonly used. Potential hotspots that were on commonly used routes were chosen for our zones. With these zones, we counted how many violations from each of the three surrogate measures occurred in each zone by referencing each respective cluster map. After obtaining the counts of events for harsh braking, harsh cornering, and speeding for all twenty of the zones, we also collected the number of crashes, both reported by FM and TREDS, that occurred in each zone. The first ten zones and their event and crash counts are shown in Table II.

Figure 2. Twenty Defined Zones on UVA Campus

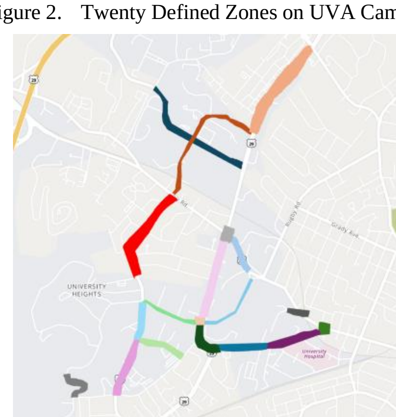


TABLE II. A SNIPPET OF CLUSTER ZONES WITH SURROGATE MEASURE COUNT AND CRASH COUNT

Location	Harsh Braking	Harsh Cornering	Speeding	FM Crashes	VA Crashes
Alderman (AFC)	6	700	46	0	5
Alderman (Church)	0	229	648	0	33
Alderman (Dorms)	0	4	41	0	0
Carr's Hill	6	24	9	2	7
Copeley Rd	2	266	463	0	36
Emmet McCormick Ramp	0	223	2	1	11
Emmet St N (Carruthers Hall)	3	1841	2	1	2
Emmet St S (Central Grounds)	2	116	474	4	3
Emmet ST S-Ivy Rd Intersection	2	189	3	0	6
Emmet St S-Stadium Rd Intersection	0	95	136	1	9

From our list of twenty zones, we had to remove the zone containing the headquarters of UVA Facilities Management. When looking at the FM crash, it was found that all the crashes in this zone were minor parking lot incidents, thus lacking the genuineness of safety risk associated with the crashes. Other low-speed collisions, those occurring with speeds less than 5 mph, were removed to be consistent with surrogate measure event data.

To find the surrogate measure with the highest correlation to crashes, we performed three separate correlation analyses for each of the measures. We only incorporated the FM crash data for this step because the surrogate measure violations were only based on FM fleet vehicles.

After obtaining the surrogate measure with the highest correlation to FM crashes, we determined that the low correlations found were due to the low number of crashes from FM. Thus, we decided to incorporate a Z-score analysis as it normalizes the measures and allows us to aggregate these normalized measures for identifying safety hotspots. For each surrogate measure, we calculated the Z-score (z) for each of the events by subtracting the surrogate measure mean ($\bar{x}$) from the event count (x) and then dividing that by the measure's standard deviation (S.D.) (1).

$$z = \frac{x - \bar{x}}{S.D.} \quad (1)$$

For each zone, we added up the z-score for its harsh braking, harsh cornering, and speeding count to constitute a final score. This accounted for normalizing the surrogate measure event numbers, as some surrogate measure events occurred more than others. In addition, this approach differs from the study Shen and his research team performed, as they added up the raw surrogate measure event number [8]. After calculation, we ranked the zones based on the final score. With our final ranked list of cluster zones, we took the three highest-scoring zones and analyzed each area. In addition, we qualitatively validated these three zones by verifying that they had VA crashes recorded. The reasoning for taking the top three is that selecting high-frequency crash zones can exhibit patterns that are less discernible in lower-frequency crash zones. After analyzing the three areas, we were able to come up with a list of potential countermeasures that FM could implement to improve safety at the University of Virginia.

V. Results

A. Surrogate Measure and Crash Analysis

Using R Studio, the results of the correlation analysis for all three of the surrogate measures and FM crashes are shown below in Table III. For FM crashes, the highest correlated surrogate measure is speeding, with a correlation of 0.29, indicating a weak positive correlation. Harsh braking had an even weaker correlation at 0.01. On the other hand, harsh cornering shows weak and negative correlations with crashes with a correlation coefficient of -0.03, implying that the harsher cornering, the fewer the accidents. This fact contradicts the literature review above, which stated that harsh cornering and harsh braking are strongly correlated with crashes [7] [12].

TABLE III. Correlation Coefficients For Surrogate Measures Against FM Crashes

Surrogate Measure	Correlation with FM Crashes
Harsh Braking	0.01
Harsh Cornering	-0.03
Speeding	0.29

After deducting low correlation due to low crash data, we calculated the mean and standard deviation for each of the surrogate measures as shown in Table IV. Harsh braking had the lowest event mean at 2.11, while harsh cornering had the highest at 258.58, highlighting a need for normalization. Thus, we incorporated the means and standard deviations to calculate the z-scores for each of the events, eventually adding these up for a final score and then ranking the zones based on the final score, as seen in Table V. Based on the table, Carruthers, Alderman Rd at AFC, and McCormick Rd. (Old Dorms) were the identified hotspots that we deduced to be the most prone to crashes, with the highest three final scores of 3.58, 2.96, and 2.50 in that order. The next highest zone was Massie Rd, with a final score of 0.94, as shown in Table V. All three of these hotspots have VA crashes, McCormick Rd having eight, Alderman by AFC having 5, and Emmet St N by Carruthers Hall having 2 crashes.

TABLE IV. Mean and Standard Deviation For Surrogate Measures

Surrogate Measure	Mean	Standard Deviation
Harsh Braking	2.11	1.97
Harsh Cornering	258.58	416.58
Speeding	216.26	317.82

TABLE V. Top Five Hotspots Based on Final Z-Scores

Location	Harsh Braking	Harsh Cornering	Speeding	FM Crashes	VA Crashes	Final Z-Scores
Emmet St N (Carruthers Hall)	3	1841	2	1	2	3.58
McCormick Rd (Old Dorms)	2	336	1116	2	8	2.96
Alderman (AFC)	6	700	46	0	5	2.50
Massie Rd	2	248	541	0	2	0.94
Carr's Hill	6	24	9	2	7	0.76
Copeley Rd	2	266	463	0	36	0.74

B. Hotspot Crash Surrogate Measures

After identifying the safety hotspots through the method listed above, we visited these areas. At each location, we noted the surrounding area and looked for potential indicators of why there was a high risk of crashes. Indicators include the speed limit, traffic signs like pedestrian crossing signs, traffic lights, sharp corners, speed bumps, and others. We also took note of the lack of these indicators, which could be the cause of crashes or a high rate of surrogate measure violations, specifically speeding. Our findings are shown in Table VI.

TABLE VI. Analysis of Proposed Hotspots With Asterick* Indicating Both Sides of the Road

Safety Hotspot	Existing Countermeasures	Lack of Indicators
Emmet St N (Carruthers Hall)	1. 1 Speed Limit Sign*	1. Right turn lane into Carruthers Hall 2. Right turn ahead sign 3. Electronic speed indicator 4. Widened Road in Carruthers Hall entrance
McCormick Rd (Old Dorms)	1. 1 Speed hump with Pedestrian Crossing sign* 2. 5 Cross walks	1. Electronic speed indicator 2. Light up pedestrian signal 3. Additional pedestrian crossing signs
Alderman (AFC)	1. 3 Pedestrian crossings 2. 1 Pedestrian crossing sign with lights* 3. 1 Speed limit sign*	1. Widening of roads 2. A singular pedestrian crosswalk with lights to avoid confusion

With the list of these safety hotspots and the notes regarding potential indicators and lack of indicators, we researched different countermeasures that could help reduce the risk of crashes in those locations. Further discussion of the lack of indicators and the proposed countermeasures is followed in the next section.

C. *Countermeasures*

Countermeasures are essential for enhancing safety in identified hotspots, especially considering the University of Virginia's predominantly low-posted speed limit roads with numerous crosswalks. Previous research categorized effective countermeasures into four groups: speed management, temporal and spatial separation of pedestrians and vehicles, and improving pedestrian visibility. These four defined groups of countermeasures can be obtained through the addition of traffic signs, speed bumps, pedestrian crossing, visibility of traffic signs, and the narrowing of roads [1]. Chen et al. evaluated the effectiveness of these countermeasures in New York City, observing reductions in crash rates following implementation. Significant crash rate reductions were noted with measures such as pedestrian fencing, increased visibility of signs, extension of crossing times, and traffic signal installation [13].

Based on the literature review, we combined geofencing techniques and surrogate safety measures to identify safety hotspots and place countermeasures to improve safety at the University of Virginia campus.

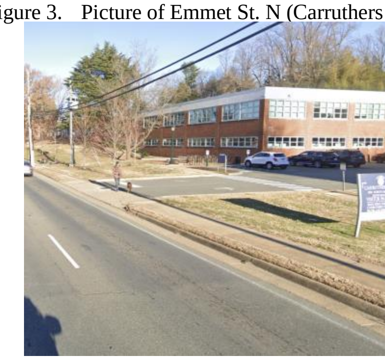
VI. Discussion

Our analysis and results differ from our literature review of past studies. Harsh braking, harsh cornering, and speeding were thought to be strong surrogate measures for crashes before the study; yet all displayed weak correlations close to zero with FM crashes in our study. This can be explained by the limited amount of crash data available, as many of the zones had zero FM crashes reported. With small counts of crashes, there is a higher likelihood of fluctuations having a disproportionate impact on the calculated correlation coefficient. This can lead to varying conclusions about the strength and direction of the relationship between our variables.

Due to the uncertainty of our correlation analysis, we shifted our focus to a Z-score analysis in order to determine our safety hotspots. As shown earlier, our surrogate measures had widely varying means and standard deviations, with a much greater number of harsh cornering and speeding events when compared to harsh braking events. To avoid bias due to surrogate measure volume, we used z-score normalization. The results gave us the zones that deviated the most from the mean, which indicates the zones most prone to safety violations.

Shifting the focus to countermeasures, our analysis includes several recommendations based on identified risk factors at different hotspots.

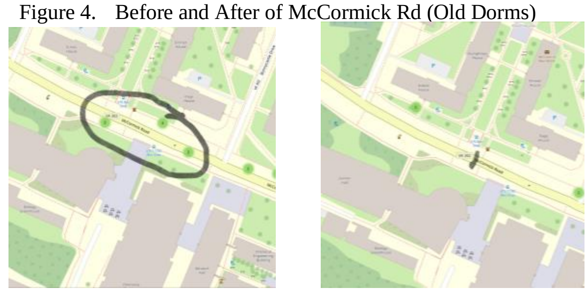
Figure 3. Picture of Emmet St. N (Carruthers Hall)



Emmet St N (Carruthers Hall): We noticed that the turn into Carruthers Hall comes without a warning and is positioned awkwardly just before a stoplight, as seen in Figure 3. With a speed limit of 40 mph, FM drivers often corner harshly to navigate the turn (1841 events). To counter this, we propose the addition of a right turn lane into Carruthers Hall, which, according to past studies, can reduce crash occurrences by 30% at similar intersections [15]. We believe this implementation would significantly decrease both the number of harsh cornering events and the risk of crashes in this zone.

McCormick Rd (old dorms): Harsh cornering, harsh braking, and speeding violations are all present at this zone. However, recent upgrades, including two-speed humps and enhanced pedestrian crosswalks, were introduced, in the summer of 2023 to counter the violations. Preliminary data from FM indicates these measures are reducing these surrogate measure events, though more analysis and data are needed for confirmation. Figure 4, showing the before and after of harsh braking events on McCormick Rd., shows no harsh braking events since the upgrades added.

Figure 4. Before and After of McCormick Rd (Old Dorms)



Alderman Rd (AFC): This location is prone to violations of harsh braking and cornering associated with its multiple sharp turns. The widening of roads around these turns can reduce harsh cornering events. The current pedestrian crossing set up with two parallel pedestrian crossings in proximity, with only one of them having pedestrian crossing lights, as seen in Figure 5, contributes to the harsh braking, based on student experience. Simplifying this into a single, well-signaled crosswalk could enhance both driver and pedestrian safety.

Figure 5. Picture of the Alderman at AFC Zone

VII. Conclusions

With the increase in vehicle technology and drivers on the road, the number of safety infractions and the potential for motor vehicle crashes increases. This study sought to enhance the safety of roads at UVA by identifying and addressing safety hotspots most prone to crashes through the analysis of geo-location and telematics data. An approach to reducing the occurrence of motor vehicle crashes was used by utilizing FM's Geotab data to identify safety hotspots and prescribe evidence-backed countermeasures to reduce the potential for safety violations and crashes at these spots. Our methods, backed up by literature review, first incorporated a correlation analysis between the safety surrogate measures harsh braking, harsh cornering, speeding to FM crashes, and then a Z-score analysis which normalized and combined the surrogate measure events. This allowed us to pinpoint these areas of high risk of accidents and underscored a need to set countermeasures aimed at reducing surrogate measure events. Upon visiting the three identified hotspots, Carruthers Hall, McCormick Rd (Old Dorms), and Alderman Rd at AFC, we observed potential risk indicators and absent countermeasures, leading to the suggestion of creating a right turn lane for Carruthers Hall, widening of roads, as well as simplifying crosswalks for Alderman Rd. We also established a baseline for evaluating the effectiveness of recent countermeasures put in place to improve the safety of McCormick Rd.

Our research contributes to the vehicular safety field by providing a framework for identifying hotspots and implementing countermeasures using Z-score analysis. Our findings contribute to UVA Facilities management's goal of ensuring safety and sustainability in their Fleet vehicles, assisting them in their commitment to the UVA 2030 Sustainability plan.

VIII. Future Work

Additional work can be done to identify different hotspots on the campus further beyond utilizing cluster maps. Firstly, geofencing can evolve beyond a simple area division, to account for vehicles' miles traveled. This would refine hotspot normalization by accounting for traffic density and time of day variations. Different telematic technologies can be incorporated for telematics technologies to capture more granular location data, as Geotab's location data is only pinged for 15 seconds. Options such as the Internet of Things (IoT) technology like LoRa Gateway nodes can be used for real-time tracking. Further analysis could explore alternative data normalization methods. While this research incorporated Z-scores to normalize the data, other general options, such as ranked-based normalization and quantile normalization can be incorporated. Additionally, more specific to this example, the total number of events and crashes could be divided by the total number of vehicles that drive through the area. This method may offer a more standardized comparison of the surrogate measure counts, accounting for varying traffic volumes across zones. Temporal patterns of surrogate measure events also should be considered, especially during high pedestrian traffic times related to university schedules. A detailed temporal analysis can reveal when certain surrogate measures are at their peak and can open the door for time-sensitive countermeasures. This tailored approach can further assist FM with its goal of enhancing road safety by extending beyond currently provided recommendations. Finally, because FM has many different types of vehicles, from trucks to sedans, research looking into which type of vehicles causes more surrogate measure events and is most prone to accidents.

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