TRB Annual Meeting

Safer Streets Priority Finder: Building A Dashboard For Vulnerable Road User Safety Analysis and Prioritization

--Manuscript Draft--

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Manuscript Classifications:	Pedestrians, Bicycles, Human Factors; Bicycle Transportation ACH20; Safety; Pedestrians ACH10; Safety; Planning and Analysis; Transportation Planning Analysis and Application AEP15; Decision Tools; Safety; Safety Performance and Analysis ACS20; Crash Analysis; Crash Data; Crash Prediction Models
Manuscript Number:	
Article Type:	Presentation and Publication
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SAFER STREETS PRIORITY FINDER: BUILDING A DASHBOARD FOR VULNERABLE ROAD USER SAFETY ANALYSIS AND PRIORITIZATION

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Word count: 7,154 words + 1 table * 250 words = 7,404 words

Submission Date: August 1, 2021

ABSTRACT

Vulnerable road user traffic deaths in the United States have increased in number and proportion over the previous decade. This growing disparity points to a larger need to prioritize safety for vulnerable road users on our streets. Evaluating and predicting vulnerable road user crash risk is a data-intensive and complex process. This study aims to make safety analysis for vulnerable road users easier and more accessible by (1) developing a modeling framework with minimal data input needs, (2) converting model outputs into cost equivalents to better link the results to planning and project scoping processes, and (3) building this functionality into an online tool and dashboard.

In this paper, we develop an approach to modeling vulnerable road user crash risk that uses Bayesian probability updating and Markov chain Monte Carlo simulations to blend an existing published statistical model with simple roadway and crash data inputs, which we built into an online tool and dashboard called the *Safer Streets Priority Finder*. We apply the tool to crash data from the City of New Orleans and describe the application of model outputs for both roadway safety planning and transit planning use cases. The paper includes validation results for New Orleans and two other jurisdictions. Overall, we found that this modeling approach performs as well or better than Sliding Window Analysis and traditional High Injury Networks, and the tool has the potential to make safety analysis easier and more accessible to planners and engineers.

Keywords: Pedestrian Safety, Bicyclist Safety, Systemic Safety, Traffic Safety, Public Health, Risk Assessment, Crash Risk, High Injury Network

INTRODUCTION

Over the previous decade, pedestrian and bicyclist traffic deaths have increased by over 50%, while overall traffic deaths decreased by 7.9% [1]. Vulnerable road users (VRUs) comprise an increasing fraction of all traffic deaths, growing from 12.6% in 2003 to 19.5% in 2018 [1], despite walking and bicycling combined representing less than 12% of all trips made in 2017 [2]. This growing disparity points to a larger need to prioritize safety for VRUs. In response, jurisdictions have embraced initiatives (such as Vision Zero) to reduce or eliminate serious crashes. These initiatives rely on understanding the safety needs of pedestrians and bicyclists, and proactively and systemically addressing those needs across our roadway networks.

While bicyclist and pedestrian crashes are too common and increasing year-to-year, they are statistically rare. This makes evaluating and predicting VRU crash risk a data-intensive and complex process. This study aims to make safety analysis for VRUs easier and more accessible by

(1) Developing a modeling framework that can estimate risk on individual network segments using widely available inputs, such as USDOT's existing Pedestrian Fatality Risk Map [3],
(2) Converting outputs into cost equivalents to better link the results to planning and project scoping processes, and
(3) Building this functionality into an online tool and dashboard that makes the results accessible to practitioners without sophisticated statistical or geospatial skills.

This paper is organized as follows. First, we provide a brief scan of research related to evaluating crash risk on a network for VRUs. Next, we describe the modeling approach and methodology that were developed and built into a free and open-source web tool and dashboard called the *Safer Streets Priority Finder* (SSPF) [4], including a brief validation of the tool's output. We present an application and use case for this tool in the City of New Orleans. Finally, we share conclusions and recommendations for future work.

LITERATURE SCAN

Over the last two decades, many US cities and states have enacted plans and policies to encourage active transportation. However, between 2009 and 2018, the number of pedestrian and bicycle fatalities nationwide has continued to trend upward, with 2018 as the deadliest and costliest year for both cyclists and pedestrians since 1990 [5]. In response, jurisdictions have embraced initiatives to reduce or eliminate serious crashes involving vulnerable road users. A key need of such initiatives is better understanding the safety needs of VRUs, which in turn calls for analytic tools for evaluating and predicting crash risk. A growing body of research has emerged documenting methods for crash analysis and predictive modeling. This literature scan summarizes current analytic methods and modeling approaches relevant to active transportation safety analysis and identifies gaps in knowledge and barriers to practice which the resulting tool seeks to address.

Previous analyses have identified the locations of past crashes within a given geographic area, typically focusing on either top crash corridors overall or "hot spots" (typically intersections) where crashes have occurred with high frequency [6] [7] [8]. Hot spot analysis is useful for understanding the scope of the problem, can highlight specific, problematic locations and/or roadway elements with high crash volumes, and is a relatively simple analytic technique. Statistical tools may be applied to confirm crash clusters are significant [9] [10].

Hot spot analyses can identify locations (intersections, neighborhoods, roadway classifications, etc.) with a disproportionate share of crashes within a dataset [11] [12] [13] [14] [15]. However, it can fail to reveal corridor-wide problems and tends to be less effective for pedestrian and bicyclist crashes, which are relatively rare and may have insufficient data to identify high-frequency crash locations. Bayesian statistical techniques can help to address this limitation by representing prior uncertainty about model parameters with a probability distribution, providing a more nuanced inferences about limited data [16]. Moreover, such analyses are based entirely on previous crash history and spatial proximity and may not consider systemic factors which are likely to contribute to crash incidence in the future.

In response to the limitations of simple crash frequency analysis, many cities have turned to the development of High Injury Networks (HIN) as a conceptual tool to characterize and develop effective crash reduction programs for urban environments [17] [18] [19] [20] [21]. The goal of an HIN is to identify a limited subset of streets where serious crash density is highest. Siding window analysis is a key analytic tool for development of a HIN, used to identify crash clusters within flexibly-sized "windows" representing overlapping segments along a street network rather than crashes at discrete locations, using previous crash history and linear proximity, while potentially capturing some elements of systemic risk. Sliding windows allow us to generalize the locations of crashes, reflecting the stochasticity in where crashes occur, while still respecting the fact that locations along corridors tend to share characteristics. The result is a flexible measure of crash density which allows for more consistent evaluation of crash injury distribution, which can greatly aid in project prioritization [22]. However, this technique requires advanced GIS capabilities and a robust network dataset, and still relies exclusively on prior crash history. Ultimately, a HIN only identifies areas where a disproportionate share of injurious crashes has already occurred; it may not account for factors likely to impact future risk. Particularly in the context of ongoing rapid changes to roadway networks, improved, predictive analytic methods that look at the underlying characteristics of streets, rather than just past crash incidence, are also needed.

The systemic safety approach recognizes the limitations of looking at crash history alone; instead, networks are screened for conditions linked to crash outcomes – whether any one of those locations specifically have had crashes. Systemic evaluation involves the identification of which built environment and contextual factors influence crash frequency and severity and the degree of this influence [23] [24]. As a result, the entire roadway network may be screened to determine where crashes are more likely to occur, even if those locations show no crash history. A variety of studies have identified potentially significant factors, including traffic characteristics, land use attributes, transit access, and socioeconomic characteristics [25] [26] [27] [28] [29] [30] [31] [32] [33] [34].

However, many of the tools available for systemic safety analysis have heavy data input requirements or require sophisticated geospatial or statistical techniques; both become barriers for agencies and jurisdictions aiming to reduce or eliminate deaths and serious injuries on their roadways [35]. Operationalizing findings from systemic analyses identifying significant factors presents additional challenges. Development of many analytic tools to assess and address traffic risk (e.g., Safety Performance Functions, Crash Modification Factors, areawide crash rates) require exposure data which most jurisdictions currently lack [36] [37].

Mansfield et al. [3] combined the facility-level factors (transportation system), neighborhood-wide data, and pedestrian fatality records from the Fatality Analysis Reporting System (FARS) between 2012-2016 to anticipate pedestrian fatality risk at census tract level across the US, and utilized the results to develop a statistical model of fatal pedestrian crashes nationwide and a map viewer of the estimated number of fatal pedestrian crashes in each Census tract. This model considers various factors to estimate risk for pedestrian fatalities, including Vehicle Miles Traveled (VMT) density by roadway functional classification, intersection density, employment density, residential population density, activity mix index, and sociodemographics. This model was validated against a HIN for Los Angeles, showing the model applied in this research combined with HIN can significantly capture high-risk area, and forms the foundation of the SSPF. However, this model does not link results to specific network locations, which is a missing element allowing practitioners to prioritize projects.

Overall, pedestrian and bicycle safety analysis has advanced considerably in recent years, providing a variety of complementary tools for analyzing crash data and a robust suite of research identifying potentially significant factors which may be used to develop predictive crash models. However, some analytic approaches lack specificity at a sub-corridor level or do not account for built environment factors and cannot provide significant insight into the root causes of crash risk. Moreover, performing more sophisticated analyses often involves large data requirements and requires adoption of advanced data mining and analytic techniques, for which local jurisdictions lack capacity. Finally, most analyses lack clear methods for linking model outputs to planning processes. Inputs for benefit-cost analyses, such as of a “no-build” cost value, are needed to help local and state officials and practitioners to make defined, targeted decisions around small-area and corridor-level investments with the greatest potential to prevent serious injuries and fatalities for vulnerable road users, and to provide end users with a means of calculating associated costs of inaction where risks have been identified.

ANALYSIS APPROACH AND METHODOLOGY

As described in this paper’s introduction, our team’s goal for this project was to develop a method that could estimate risk on individual network segments using widely available data, to link the outputs to crash costs, and to embed any advanced geospatial processing in a user interface to make the analysis more accessible to practitioners. The USDOT Pedestrian Fatality Model (PFM) achieved some, but not all, of our project’s objectives [3]; it estimates pedestrian fatality risk using publicly available data with coverage of the entire US using an output unit that links to cost. The inputs reflect a broad range of factors associated with pedestrian deaths, including roadway conditions (functional class, VMT density, intersection density), land use characteristics (destinations, density), demographic/economic characteristics (race, ethnicity, age), and exposure correlates (transit/walking commuting) [3]. However, the tract-level model couldn’t account for variation within each tract; nor could it resolve risk for the busy arterials that define tract boundaries.

The project team developed a method that built from the PFM, translating its tract-level outputs into segment-level estimates. Sliding window analysis, the precursor to developing a HIN, generalizes risk along corridors that tend to share similar characteristics—a gesture in the direction of systemic analysis, even if the specific roadway risk factors are not analyzed. Our approach blends the PFM outputs with a Sliding Window process to transpose outputs onto the network. By combining these two approaches, we built an analytical framework that incorporates systemic pedestrian environment issues with observed crashes.

For the model to be effective and appropriate, it needed to 1) be able to function with a limited amount of observed crash data, 2) be able to incorporate existing and future work into its process, 3) be scalable at the national level, 4) provide information and a clear, understandable output for users with limited technical capabilities.

To achieve these goals, the project team determined a Bayesian approach would be most suitable. Amongst other reasons, a Bayesian approach exhibits the following traits:

- Conducive for merging multiple models into one.
- Allows for implementation of prior information into the model, rather than a reliance on purely observed data.
- Has no limit on the amount of data needed to create an estimate.
- Allows for easy updating of results as more information is gained over time (i.e., as crashes are observed).
- Allows for adjustment by tuning parameters, and relatively easy expansion of the model in future work.

Sliding Window Analysis

Sliding Window Analysis is used to summarize crashes on the network by mode and severity. Windows are set to 0.5mi (800km), and they are stepped through the network in 0.1mi (160m) increments. The window segments containing counts of crashes by mode and severity along them form the unit of analysis for the model described below. Additionally, a severity-weighted crash score is calculated for each mode for building a traditional HIN, and the output is provided separately from modeled outputs in the SSPF interface.

Model Formulation

The Bayesian Network Model (Network Model, or NM) is formulated to estimate the expected rate of crashes by mode and severity for each window segment, given the following inputs:

1. The observed crashes by mode and severity on each window segment and in each tract,
2. PFM output for the area containing the segment, and
3. National crash rates per mile for the functional class within the window segment.

The latter two pieces of information are used to calculate our Bayesian Priors. The observed crashes in each tract and on the window segment are then used to update this information and estimate a posterior likelihood of crashes occurring on the window segment. The NM itself contains two sub-models. Both sub-models utilize compound distributions--a Gamma-Poisson and a Beta-Binomial. In both instances, conjugate priors are used to ensure the approach is both updatable and tractable.

Model 1

The first sub-model (NM-GP) uses a Gamma—Poisson distribution to estimate the number of crashes occurring in each Census tract, using the PFM output as a prior, which factors in variables related to both roadway risk and exposure. This model is applied separately for each mode and severity (note that PFM output – estimate of fatal pedestrian crashes – is used as a prior for all modes and severities). The model is formulated as follows:

Let:

- y_t = number of observed crashes in the past N_o years in Census tract t
- pfm_t = PFM output of annual fatal pedestrian crash rate p in Census tract t

- N_o = number of years over which crashes have been observed – typically 5
- N_w = number of years equivalency used to weight PFM-based prior – equal to N_o for fatal and serious injury crashes, and $\frac{N_o}{5}$ for lower severity crashes

The prior distribution for each tract is defined by shape parameter α_0 and rate parameter β_0, defined as follows:

- $\alpha_0 = pfm_t * N_w$
- $\beta_0 = N_w$

Then these values are updated to incorporate observed crashes:

- $\alpha = \alpha_0 + y_t$
- $\beta = \beta_0 + N_0$

Our final distribution is described, $\lambda \sim \gamma(\alpha, \beta)$

Model 2

The second sub-model (NM-BB) uses a Beta—Binomial distribution to allocate the tract's crashes to window segments, using national crash rates by functional class as a prior, as a proxy for roadway design elements associated with risk of both a crash occurring and the crash's outcome being severe (e.g., motor vehicle travel speeds, number of lanes, motor vehicle AADT, etc.). This model is applied separately for each mode and severity. Note that national crashes by functional class include fatal crashes only due to data availability. National fatal pedestrian crash rate per mile for different functional classes of roads are calculated using 2015-2019 FARS data and 2016 mileage data from FHWA Highway Statistics. Window segments that coincide with the boundary of a Census tract use tract-level data pooled across all adjacent tracts. The NM-BB model is formulated as follows:

Let:

- p_w = probability p that a crash within census tract t happens on window w (versus all other windows in tract)
- c_w = number of observed crashes c in tract t on window w
- $c_w{}'$ = number of observed crashes c in tract t on all other windows besides window w
- C_f = number of fatal crashes nationally C happening on functional class f
- $C_f{}'$ = number of fatal crashes nationally C happening on all other functional classes besides f
- m_f = mileage m of functional class f in the United States

The prior distribution for each window segment is defined by the number crashes, grouped into two mutually exclusive and exhaustive outcome states: "hits" (crash rate on this functional class) α_0 and "misses" (crashes per mile occurring on *other* functional classes) β_0.

- $\alpha_0 = \frac{C_f}{m_f}$

- $\beta_0 = \frac{c_f{}'}{m_f}$

Then these values are updated to incorporate observed crashes:

- $\alpha = c_w + \alpha_0$
- $\beta = c_w{}' + \beta_0$

Our final distribution is described, $\varphi \sim \mathrm{B}(\alpha, \beta)$

Model Combination and Sampling

Given these two distributions, we generate random samples for each mode and severity on each window segment parameterized as follows:

- $\theta = Pois(\lambda)$, which estimates expected rate of crashes in the tract per year
- $Crashes = \mathrm{B}(\theta, \varphi)$, given the expected number of crashes in the tract per year, estimates how many of them happen on this window segment

Sampling is done using the R programming language and a package called RStan [38] [39]. The core functionality of the tool is implemented in R with the user interface developed using the Shiny package [40]. RStan generates 2,000 samples across four Markov chain Monte Carlo (MCMC) simulations from each distribution for each unique combination of alpha and beta values in the study area. The results are the mean value across all samples from the binomial distribution. They represent an expected rate of crashes per year on each window segment, repeated for each mode and severity separately. Dividing by the window length in miles produces an annual crash rate per mile for each Sliding Window.

This crash rate represents the crash density which is then joined to the original street segments. This is done by first dicing the roads into short segments of 160 m (step size) long. Each short segment is then assigned the highest crash density associated with all the Sliding Windows coinciding with it. The short window crash density is then joined back to the original street segments by calculating the average crash density of its short segments weighted by their length.

Severity-Based Crash Cost

Established methodologies already exist for estimating the monetary value of deaths, injuries, and damaged property from traffic crashes, as well as the monetary cost of economic and societal impacts from crashes [41] [42]. The project team calculated national costs for crashes following the guidance set forth in Chapter 6 of FHWA's *Crash Costs for Highway Safety Analysis* (2018) [43]. Costs are applied to the estimated number of crashes by severity, following the KABCO scale (killed, injury A, injury B, injury C, or property damage Only). The tool applies a default discount rate of 3% to reflect today's value of costs projected over a five-year time horizon. Both the crash costs and the discount rate can be customized by tool users.

Calibration

Initial results from this model showed that intra-network relative distribution looked reasonable (i.e., the segments with the highest model outputs also had the most observed crashes and were consistent with local transportation practitioners' understanding of high-risk portions of the network). However, the magnitude of crashes and corresponding costs, if summed across the network, tend to be higher than observed values over an equivalent period (2-3 times higher in urban areas, and much higher in rural areas). To account for this difference, we scaled the output crash estimates so the total crash cost from model outputs for each mode in the entire study area is the same as the observed crash cost.

Validation

To evaluate the utility of the Safer Streets Model relative to HIN for correlating with future (i.e., out-of-sample) crashes and identifying priority investment areas, our team developed a validation methodology that compared analysis outputs run on 2010—2014 crash data to crashes observed between 2015 and 2019 (i.e., out-of-sample). Model outputs are compared to those of the Sliding Window Analysis to observe if the model outperforms the Sliding Window Analysis in identifying the segments that have crashes from the validation set.

The input set is run through the tool's Sliding Window Analysis and model components. The validation set is put through the Sliding Window process in the tool. The results from each of these processes are joined to the road network and segmented by Sliding Windows in the same manner. This minimizes any biases introduced by the Sliding Window process in the way crashes are counted. For each street segment, this creates three outputs for every unique combination of mode and severity:

1. Sliding Window Analysis using 2010—2014 crashes
2. Safer Streets Model using 2010—2014 crashes
3. Sliding Window Analysis using 2015—2019 crashes

Street segments are sorted based on the outputs from either 2010—2014 Sliding Window Analysis (outcome 1 above) or the Safer Streets Model (outcome 2). For various percentile groupings of streets on these two outcomes, we summed the proportion of outcome 3 that falls within this subset of the network. For example, in the top 5th percentile of the network according to outcome 1, what percent of the 2015—2019 crashes falls on this network subset? We repeated this calculation for twenty different percentile thresholds (ranging from 5th to 100th in 5% increments) across four crash groupings: severe pedestrian crashes (Killed plus Injury A, or K+A), all pedestrian crashes, severe bicycle crashes, and all bicycle crashes, and across three different jurisdictions: The City of New Orleans, LA; Lincoln Parish, LA; and the City of Lowell, MA.

Table 1 summarizes the results. Columns 2—3 show the cumulative outcome 3 findings for the 10th percentile network, columns 3—4 show the same for the 25th percentile network, and columns 5—6 contain cumulative distribution diagrams showing all results from 5% to 100% of the network. Across the board, we saw that for every subset of the network, the Safer Streets Model's subset contained an equal or larger share of the out-of-sample crashes than the Sliding Window Analysis. For example, for New Orleans severe pedestrian crashes, 17% of outcome 3 was contained in the top 10% of the network based on the 2010—2014 Sliding Window score (outcome 1), whereas the top 10% based on the Safer Streets Model (outcome 2) contained 37% of the outcome 3 score. In Lincoln Parish, where our data contained fewer crashes due to both the rural context and missing geolocations on some crash records, the Sliding Window networks contained very few of the severe pedestrian or bicycle crashes.[1]

The magnitude of the outcomes for both models is much lower than the in-sample metrics used to characterize HIN (e.g., 70% of K+A crashes on 12% of the network). In our top 10% networks, we see the Safer Streets Model capturing 0% to 41% of the out-of-sample crashes, and the Sliding Window Analysis capturing 0% to 38%. This is expected, both because out-of-sample predictions are harder than predicting input data, and because roadway investments in higher risk areas over time should cause the relative share of crashes on this subset to decline. Nonetheless, the Safer Streets Model outperformed the Sliding Window Analysis for severe crashes in all three test jurisdictions. When looking at all crashes, the results were closer, with more instances of the two models performing about equally. None of the network thresholds for any location, mode, or severity of crashes had a result where the Sliding Window Analysis outperformed the Safer Streets Model.

Further validation is needed to compare the magnitude of model outputs to observed crashes over time and explore differences by mode and severity, but at this stage, the Safer Streets Model appears to perform comparably or slightly better than Sliding Window Analysis, so that model output may be used alongside or instead of traditional High Injury Networks for informational purposes to screen for locations that may benefit from safety investment.

USE CASE: CITY OF NEW ORLEANS, LA AND REGIONAL TRANSIT AUTHORITY

The project team developed the SSPF to address an identified need to better understand both the likelihood of serious crashes involving people walking and bicycling on the City of New Orleans' road network, as well as a means by which to quantitatively rank segments (and thus, potential interventions) and estimate the costs of those crashes, in the context of a robust suite of pending and proposed Complete Streets interventions and implementation of a transit network redesign. This section highlights how the City of New Orleans and New Orleans Regional Transit Authority have initially applied the tool to address outstanding safety questions.

Background

In 2012, FHWA designated the City of New Orleans (City) as a pedestrian safety focus city, which led to the drafting of a pedestrian safety action plan. In 2015, FHWA updated this designation to include a focus on bicycle safety as well. While this effort identified crash "hot spots" focused on severe and fatal injuries, these findings have resulted in prioritized implementation for 20 intersections. However, this effort has not led to a systemic approach to improving safety outcomes or an ability to identify and prioritize specific roadway segments and appropriate countermeasures that will have the greatest impact on human lives. Meanwhile, the City is currently engaged in the implementation of a rapid-build protected bikeway network and is interested in developing evidence-based tools for project prioritization. The City previously conducted preliminary assessments toward the development of a High Injury Network (HIN), but found this method failed to account for factors likely to impact future risk (particularly in the context of ongoing, rapid changes to roadway networks).

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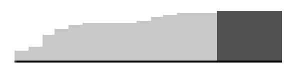
[1] Note that validation for severe bicycle crashes could not be calculated because there were no observed fatal or serious injury crashes with valid geolocations in the 2015—2019 sample.

Table 1. Out-of-Sample Validation Results for Sliding Window Analysis and Safer Streets Model in Three Test Jurisdictions

	What percent of out-of-sample crashes overlap with the top 10% of the network?		What percent of out-of-sample crashes overlap with the top 25% of the network?		Cumulative Distribution: y% of out-of-sample crashes overlap with the top x% of the network (dark gray = 100%)	
	Sliding Window	Safer Streets Model	Sliding Window	Safer Streets Model	Sliding Window	Safer Streets Model
New Orleans, LA						
Pedestrian K+A Crashes	17%	37%	42%	60%		
Pedestrian All Crashes	53%	54%	67%	75%		
Bicycle K+A Crashes	23%	34%	23%	54%		
Bicycle All Crashes	46%	53%	75%	77%		
Lincoln Parish, LA						
Pedestrian K+A Crashes	0%	0%	0%	56%		
Pedestrian All Crashes	38%	48%	38%	56%		
Bicycle K+A Crashes*	N/A	N/A	N/A	N/A		
Bicycle All Crashes	9%	29%	9%	73%		
Lowell, MA						
Pedestrian K+A Crashes	17%	41%	50%	71%		
Pedestrian All Crashes	51%	55%	74%	84%		
Bicycle K+A Crashes	3%	29%	3%	72%		
Bicycle All Crashes	41%	50%	63%	74%		

*Sliding Window and Safer Streets Model ran on 2010-2014 data; out-of-sample crashes came from 2015—2019. Out-of-sample validation for Bicycle K+A Crashes in Lincoln Parish was not possible because there were no valid geocoded fatal or injury A bicylce crashes observed in the 2015—2019 data.

In short, the City sought a means to screen for traffic safety problems across the entire street network and prioritize opportunities for high impact investment. More importantly, the City wanted a way to quantify the “bottom line” value of a proposed intervention versus the cost of no intervention. This approach would require linking the cost of investments to the mitigated costs of future injuries and fatalities prevented. Having numerical values for the costs associated with injury and loss of life would provide an important input for cost-benefit analyses and serve to highlight the impact of maintaining status-quo conditions. Finally, the City sought to better support decision-making, both for ranking and prioritizing internally-funded projects, as well as to support state and federal grant applications.

The New Orleans Regional Transit Authority (RTA) also collaborated on the development of this tool, with the intent that it can be used to evaluate a) areas where pedestrian safety enhancements along the transit network are most likely to benefit transit riders, and b) to explore additional analytic uses of the model itself, such as mapping and evaluating crashes involving transit vehicles to identify and prioritize systemic safety issues.

Application

The tool accepts users' crash data and street network data and allows them to be mapped to standardized formats the models can then use. Crash data is mapped to the ‘KABCO’ scale of severity for bicycle and pedestrian modes. Figure 1 and Figure 2 show the pedestrian and bicycle crash severities and their locations for New Orleans from 2015 to 2019.

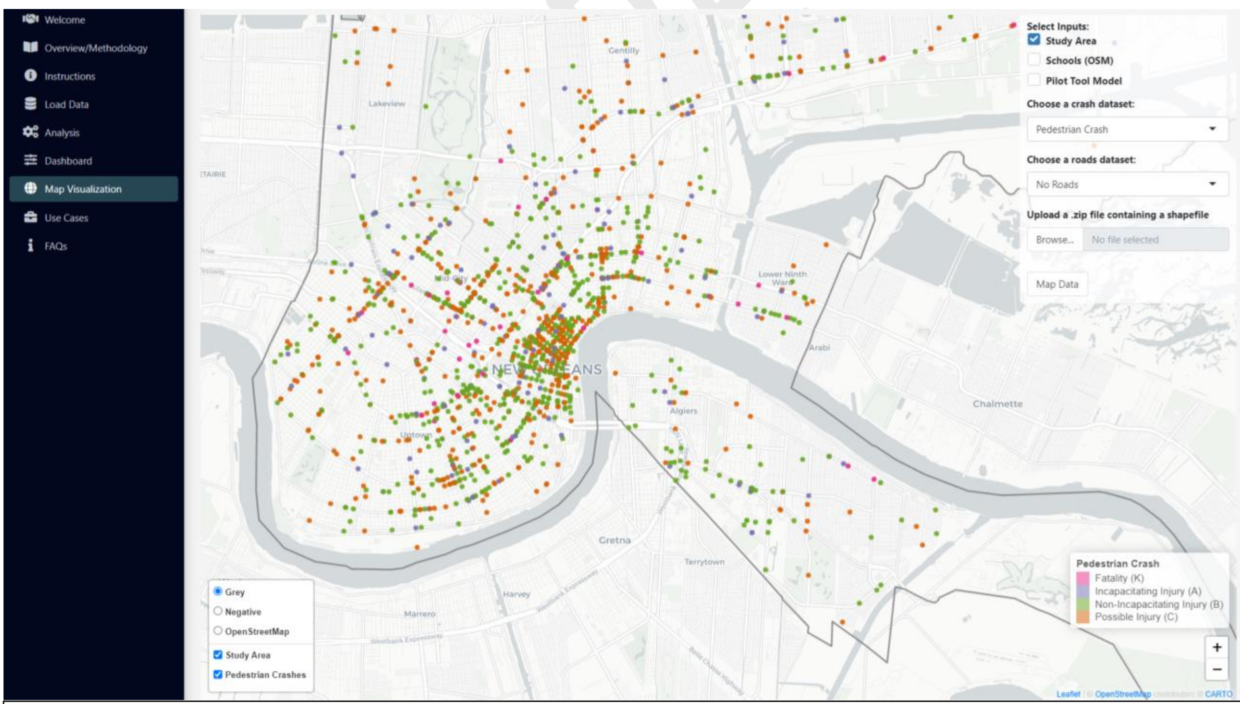


Figure 1. Pedestrian crashes in the City of New Orleans mapped by severity within the tool interface

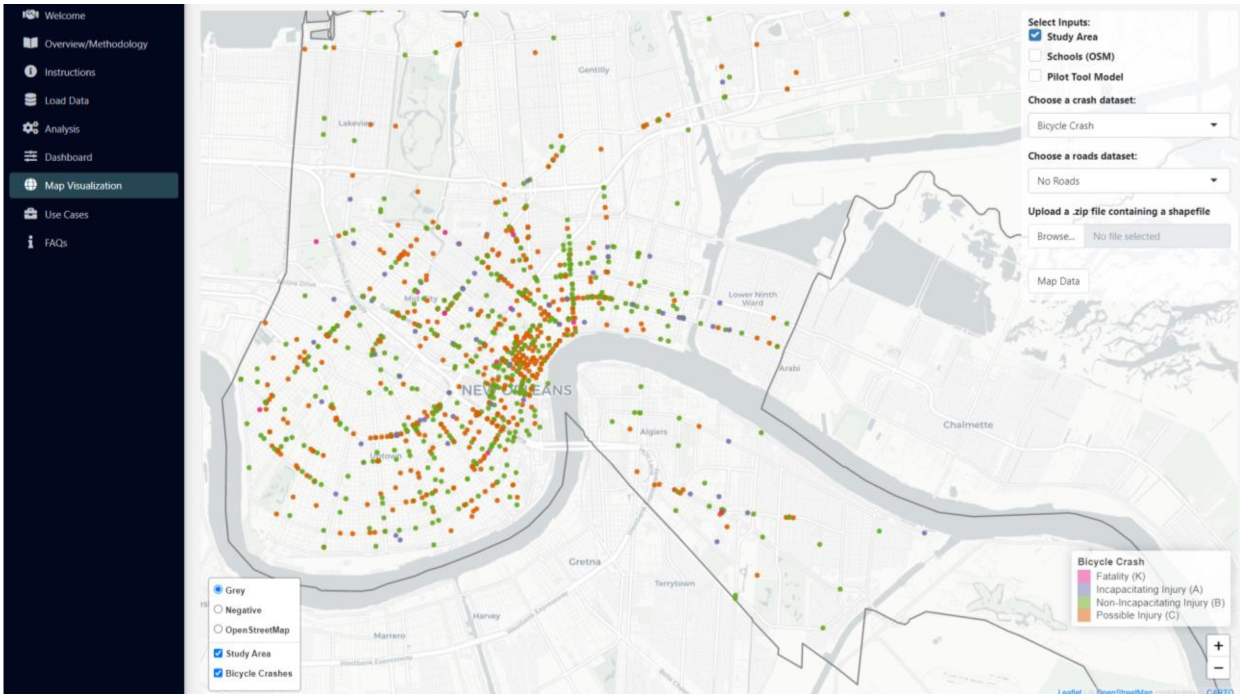


Figure 2. Bicycle crashes in the City of New Orleans mapped by severity within the tool interface

The tool's Sliding Windows Analysis feature provides an initial look at historical crash density per mile by mode (shown for New Orleans in Figure 3 on the left), while the Safer Streets model shows the estimated crash cost per mile, calculated as described in this paper (Figure 3, right). This snapshot of areas where crashes previously occurred, and their concentration, weighted by severity, provides planners with an instant visualization of the road network to compare to past crash analyses.

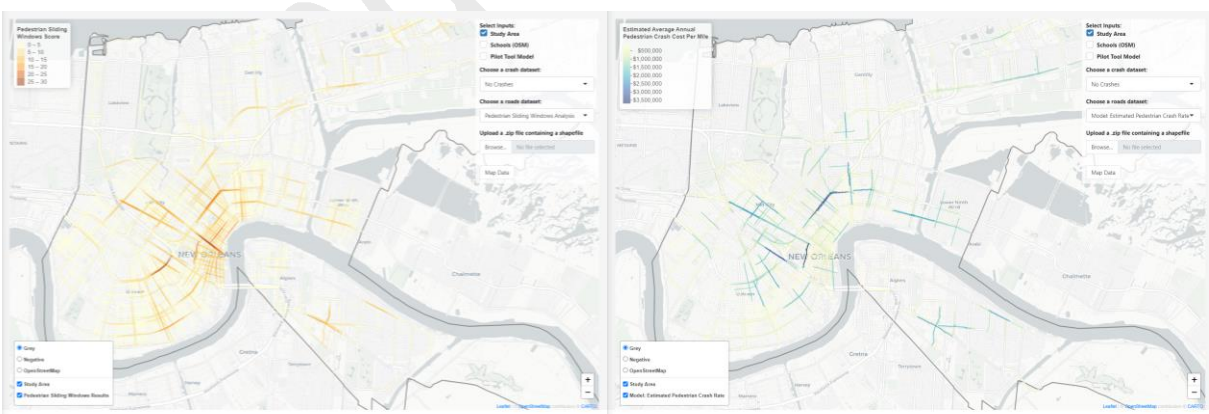


Figure 3. Sliding Window Analysis (left) and Safer Streets Model (right) output for pedestrian crashes

Using the tool, the City of New Orleans was able to generate an estimation of costs associated with future pedestrian and bicyclist injuries and deaths if no action is taken to mitigate traffic hazards. In addition, the tool allows for quick visual comparison of how model outputs vary by mode: while some corridors stand out for a high frequency of serious crashes for a specific mode, other corridors stand out for being relatively crash-dense for all modes. These visualizations can support mode-specific planning efforts or multi-modal approaches to roadway redesigns. Figure 4 shows Safer Streets model output for bicycle crashes.

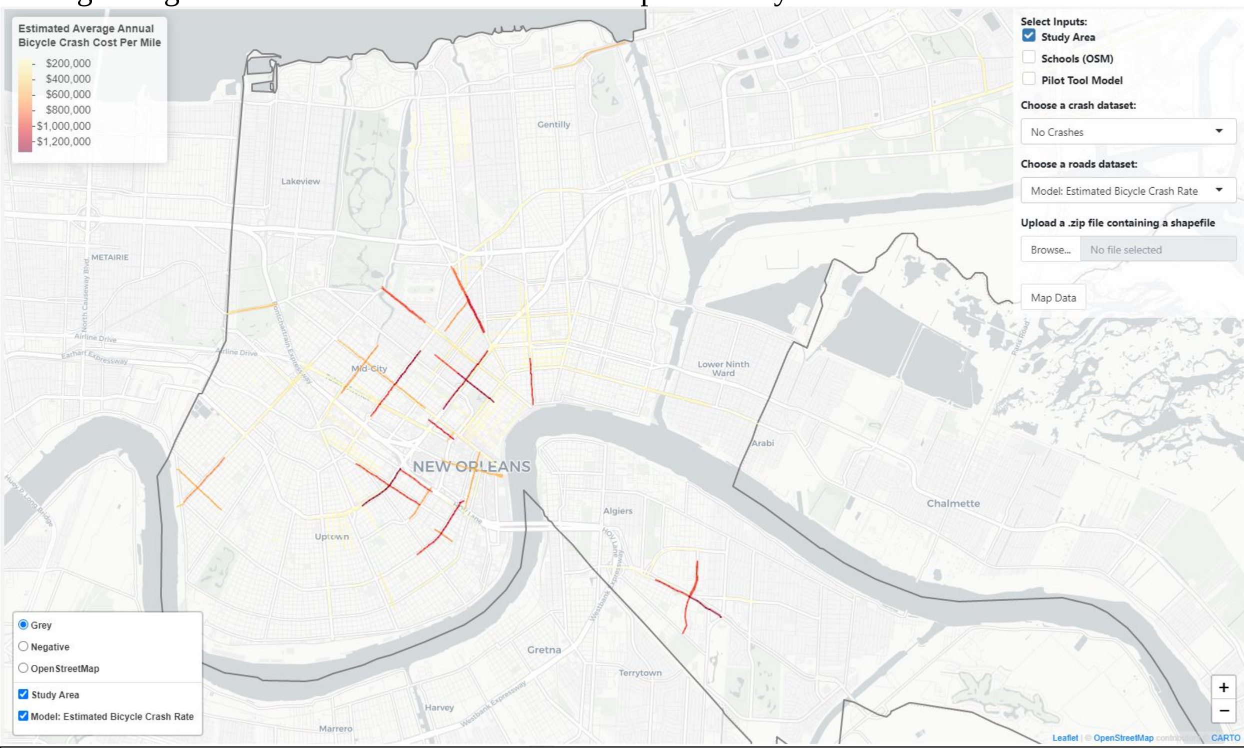


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Figure 4. Safer Streets Model outputs for bicycle crashes

These distinctions can be important in engaging the community and decision makers on safety priorities as well as targeted awareness campaigns for vulnerable road users. For example, these results have created new collaboration opportunities with key stakeholders such as the New Orleans Regional Transit Authority because some of the higher pedestrian crash densities in the Sliding Window Analysis correspond with high-ridership fixed route corridors where transit users may be at higher risk for traffic injuries. The built-in map visualization tool, moreover, allows the user to upload additional shapefiles (such as transit routes or stops) to visually assess the relationship of crash outcomes to features of interest, or the results can be exported for further analysis. The RTA is using this information to adjust station locations, improve connections to and from station locations, and lobby state and local partners to improve pedestrian amenities around its stops. Figure 5 shows Safer Streets Model output for pedestrians overlaid with existing transit stops in the study area.

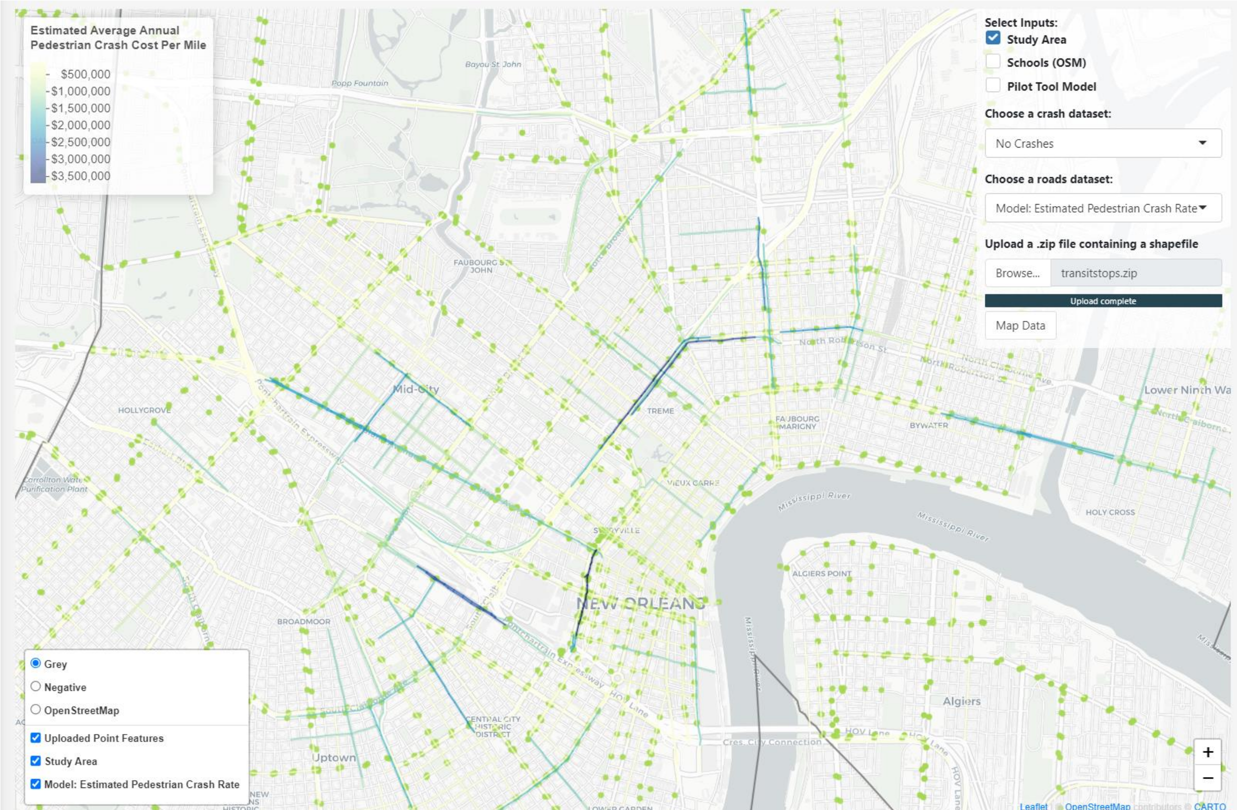

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Figure 5. Map visualizer showing outputs for pedestrian risk model, overlaid with transit stop point features

Finally, the tool dashboard and downloadable report synthesize high-level findings about the input data, including total number of crashes by year, severity, mode, and functional classification of roadway. The dashboard also identifies a concise list of Highest Crash Corridors by Sliding Window Analysis for pedestrians and bicyclists, as well as graphic representation of model fit for the dataset. These features provide a timesaving asset for citywide and neighborhood-level planning, reducing time spent on data reduction and analysis. Figure 6 shows an excerpt from the dashboard showing the distribution of crashes by mode and severity, confirming the overrepresentation of pedestrians and bicyclists among fatal and serious injury crashes.

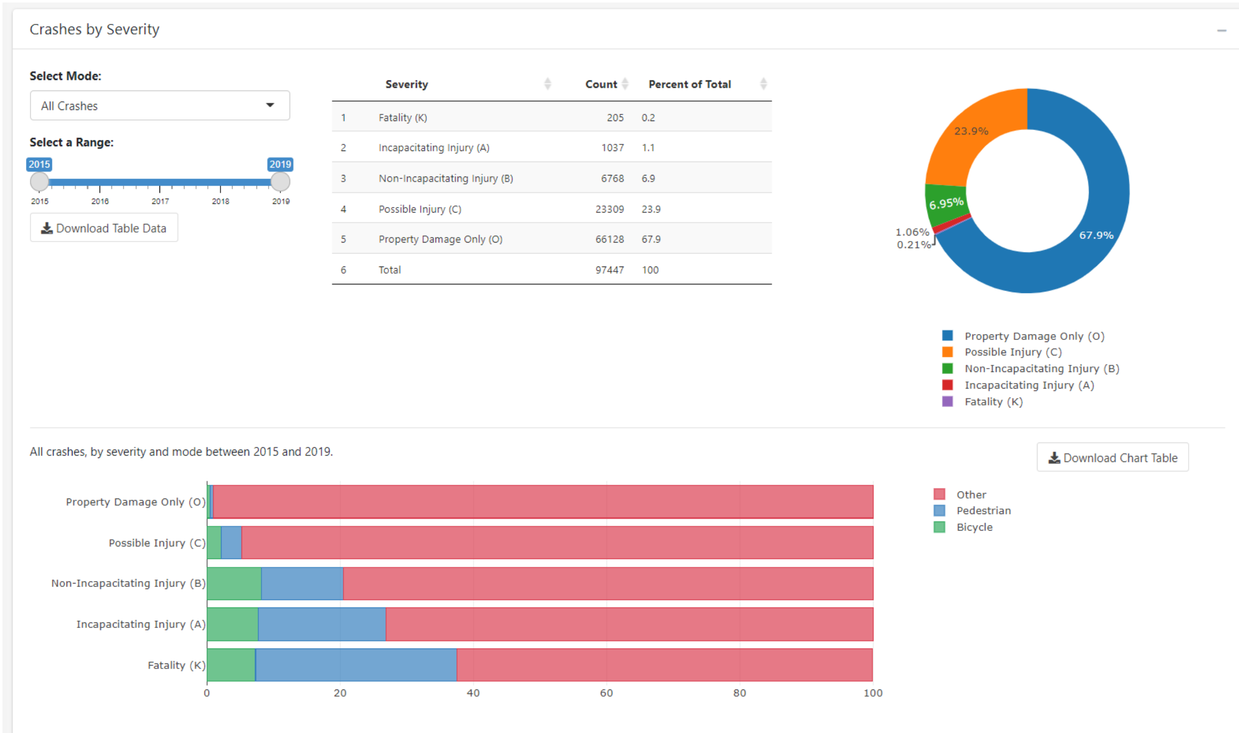

Figure 6. Dashboard excerpt displaying distribution of crashes by mode and severity

Use Case Outcomes

The City's previous approach to identifying problematic locations focused on "hot spot" analyses to derive priority locations for bicycle crash reduction strategies, and highlighted intersections rather than street segments. This approach limited the City's ability to fully leverage street improvement projects where bike facilities and other design interventions could be integrated within a corridor. The Sliding Window Analysis enables planners to more easily find streets with higher than desired crash densities and prioritize accordingly. This focus on targeted street segments enables planners to understand street design commonalities that contribute to higher crash densities, and to determine where protected bike lanes and other design interventions can be implemented to reduce severe injuries. These might include wide streets, multi-lane intersections, high traffic generators, lack of medians, or lack of sidewalks and bike lanes. This information can then be used to determine appropriate engineering countermeasures. At present, this work is largely focused on the downtown and downtown-adjacent neighborhoods of New Orleans but will expand to other areas of focus. Meanwhile, the City of New Orleans' law enforcement agencies are using this information to inform traffic enforcement and awareness programs using a "data-driven" approach.

The Regional Planning Commission, the local MPO, in partnership with the City of New Orleans is nearing completion of a local road safety plan consistent with FHWA guidance and consistent with Vision Zero initiatives across the US. Collectively, this safety plan and the tool output will guide the City's effort to move from reactive to proactive approaches that look not only at past crash histories but toward more predictive measures. This includes factoring in the cost of no action into policy decisions. The City of New Orleans is using the cost outputs estimated by the Safer Streets Model to project estimated aggregated costs across the City, specific corridors, and certain sub-areas. This information is being used to engage the community, local and state transportation agency leaders, and elected officials on the effects of inaction. It is also being used to inform project delivery goals and performance metrics in the areas most impacted.

Based on the model results, the City of New Orleans has identified a concise list of street segments where changes in the built environment to improve walking and bicycling safety are most likely to have a measurable impact on future outcomes. In this case, several of these corridors have already recently undergone safety-oriented changes or are slated for future improvement. Thus, this analysis provides a useful baseline for future evaluation of project impacts. For other corridors, the model results provide a roadmap for selecting and proposing proven crash countermeasures, allocating or securing funding, and engaging the community, local leadership, and elected officials.

Meanwhile, the RTA is using transit ridership as an additional input to identify agency priorities in discussion with City departments about future investments. Streets identified by the tool as having the highest level of risk for pedestrians coincide with some of the most important and heavily trafficked routes in the RTA system. These results highlight areas to advocate for safety improvements for RTA riders and are being integrated into an updated framework for ensuring safe and equitable pedestrian access to transit.

As future routes and improvements are planned, pedestrian walksheds will be overlaid with crash maps to ensure stops are placed in a manner that reduces walkability barriers. Additionally, the RTA plans to use the tool to visualize and analyze crashes involving transit vehicles, and incorporate tool results into operator training exercises. Having the tool to contextualize crashes involving transit vehicles could help the agency better discern if a crash occurred from operator behavior, or from high-risk road design. Collectively, the information derived from tool application can be used by the agency in approaching other city and state level agencies to identify issues and push for improvements, as well as in grant applications to help finance these initiatives.

CONCLUSIONS

The SSPF accepts simple end user input data to build two different safety analyses with varying levels of complexity and reliance on crash history versus other risk factors. Our validation efforts to date show the Safer Streets Model performs at least as well at identifying locations with fatal and serious injury crashes as the simpler Sliding Window Analysis, and in many cases outperforms it. Neither of these analyses have been validated against other types of safety analyses (e.g., safety performance functions). This tool therefore is a good entry point to safety analysis but should not replace any more advanced systemic analysis work agencies are already doing.

Outputs from the network model are expressed as costs to better link the impact of crashes to the planning process. We applied calibration factors to bring the total aggregate modeled crash cost by mode in the study area into alignment with observed 5-year crash costs in the study area. These costs are still not a perfect representation of risk on the network; they are an approximation of aggregate, long-term trends, all else equal. However, used cautiously and with an understanding of their limitations, the costs on the network can be summed or combined across corridors or study areas to estimate the potential opportunity for safety improvements.

We anticipate the primary users of this tool will be government agencies at the city or county level who are engaged directly in project prioritization and implementation. State DOTs and regional governments and entities can also use the tool by aggregating results across multiple counties to identify priority projects, inform funding requests and allocations, and support public engagement efforts. The tool's outputs may be used directly within the online application, substantially reducing the technical burden associated with safety analysis, enabling the product to be useful to a wide range of jurisdictions and users. The tool also offers spatial and safety analysis to non-governmental advocacy groups, who previously may not have had these capabilities. The tool's open-source nature will enable future developers and researchers the opportunity to expand, adapt or update components of the tool.

The project team identified multiple opportunities for future research and development, including:

- *Models & Processes*: The Bayesian model needs further validation against out-of-sample data sources and other analytical tools (e.g., safety performance functions). Future development should additionally include a model for motor vehicle crashes. Updating the PFM with newer data as well as estimating tract level models for bicycle and motor vehicle crashes would likely improve model performance.
- *Customization and User Interface enhancements*: User interface enhancements to facilitate building a High Injury Network from either Sliding Window Analysis or Safer Streets Model output, as well as additional customization and reporting, expand the default datasets available within the tool (such as pre-loading publicly available crash data); provide functionality to sum crash costs in sub-areas or corridors.
- *Usage guidance*: Develop additional use cases in collaboration with partner agencies and end users.

ACKNOWLEDGMENTS

The project work depicted in this paper was grant-funded via USDOT Safety Data Initiative (SDI; FAIN 69A34520501010620). The authors are grateful for the opportunity provided by SDI to advance data-driven safety analyses. Thanks to our peer exchange cohort and colleagues at USDOT, NHTSA, City of New Orleans, New Orleans Regional Transit Authority, City of Ruston, Louisiana Department of Transportation and Development, City of Lowell, and Toole Design for providing feedback to strengthen our work. Thanks to Dr. Mansfield and co-authors [3] for the use of the national Pedestrian Fatalities Model data and additional feedback and guidance. All opinions and errors are our own.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: Study conception and design: Jatres, Ruley, Schoner, Stickney. Literature review: Izadi, Tolford. Data collection: Finfer, Nigro, Patterson, Schoner, Tolford. Analysis and interpretation of results: Finfer, Jatres, Putta, Ruley, Schoner, Stickney, Tolford. UI development and testing: Finfer, Jatres, Patterson, Putta, Schoner, Stickney, Tolford. Draft manuscript preparation: Finfer, Izadi, Jatres, Nigro, Putta, Schoner, Stickney, Tolford. All authors reviewed the results and approved the final version of the manuscript.

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The Safer Streets Priority Finder tool and associated data outputs are provided for informational purposes only, and all results, recommendations, geographic and mapping information, and commentary contained herein are based on limited data available at the national scale or user uploaded data—user uploaded data may be from unverified sources. The project creators make no warranties, expressed or implied, concerning the accuracy, completeness, or suitability of the underlying source data used in this analysis or the recommendations and conclusions derived therefrom.

The project creators make no representation as to the accuracy, adequacy, reliability, availability or completeness of the crash records or is not responsible for any errors or omissions in such records or data. Motor vehicle crashes are complex occurrences that often result from multiple contributing factors. The data posted available within this tool, including crash data, are collected for the purpose of identifying or planning safety enhancements for potential crash sites, improving roadway safety, or improving conditions or railway-highway crossings. Under federal law, this information is not subject to discovery and cannot be admitted into evidence in any federal or state court proceeding or considered for other purposes in any action for damages that involves the sites mentioned in these records (see 23 USC, Section 409).

REFERENCES

[1] PBIC, "Facts & Figures: Safety," [Online]. Available: https://www.pedbikeinfo.org/factsfigures/facts_safety.cfm. [Accessed 29 07 2021].

[2] NHTS, "Popular Person Trips (PT) Statistics: Transportation Mode," [Online]. Available: https://nhts.ornl.gov/person-trips. [Accessed 29 07 2021].

[3] T. J. Mansfield et al., "The effects of roadway and built environment characteristics on pedestrian fatality risk: A national assessment at the neighborhood scale," *Accident Analysis & Prevention,* vol. 121, pp. 166-176, 2018.

[4] D. Patterson et al., "Safer Streets Priority Finder," 2021. [Online]. Available: https://www.saferstreetspriorityfinder.com.

[5] BTS, "Transportation Fatalities by Mode," 2020. [Online]. Available: https://www.bts.gov/content/transportation-fatalities-mode.

[6] M. Abdel-Aty and A. Pande, "Crash data analysis: Collective vs. individual crash level approach," *Journal of Safety Research,* vol. 38, no. 5, pp. 581-587, 2007.

[7] M. Brozen and D. Shockley, "Towards Best Practice Collision Analysis for Vision Zero Programs," in *TRB 95th Annual Meeting,* Washington DC, 2016.

[8] A. Jahangiri et al., "Data mining to improve planning for pedestrian and bicyclist safety," USDOT, 2019.

[9] K. Kim and E. Y. Yamashita, "Using a K-means clustering algorithm to examine patterns of pedestrian involved crashes in Honolulu, Hawaii," *Journal of Advanced Transportation,* vol. 41, no. 1, pp. 69-89, 2007.

[10] T. Tolford, J. Renne and B. Fields, "Development of a Low-Cost Methodology for Evaluating Pedestrian Safety in Support of Complete Streets Implementation," *Transportation Research Record,* vol. 2464, pp. 29-37, 2014.

[11] P. Morency and M.-S. Cloutier, "From Targeted "Black Spots" to Area-Wide Pedestrian Safety," *Injury Prevention,* vol. 12, no. 6, pp. 360-364, 2006.

[12] K. Jang et al., "Evaluation of Pedestrian Safety: Geographical Identification of Pedestrian Crash Hotspots and Evaluating Risk Factors for Injury Severity," in *TRB 92nd Annual Meeting*, 2013.

[13] N. Schuurman, J. Cinnamon, V. A. Crooks and S. M. Hameed, "Pedestrian Injury and the Built Environment: An Environmental Scan of Hotspots," *BMC Public Health,* vol. 9, no. 1, p. 233, 2009.

[14] R. J. Schneider et al., "United States fatal pedestrian crash hot spot locations and characteristics," *Journal of Transport and Land Use,* vol. 14, no. 1, pp. 1-23, 2021.

[15] C. Lee and M. Abdel-Aty, "Comprehensive analysis of vehicle-pedestrian crashes at intersections in Florida," *Accident Analysis & Prevention,* vol. 37, no. 4, pp. 775-786, 2005.

[16] S. M. Lynch, "Basics of Bayesian Statistics," in *Introduction to Applied Bayesian Statistics and Estimation for Social Scientists,* Springer New York, 2007, pp. 47-75.

[17] DVPRC, "Philadelphia Crash Analysis Standards & Recommendations," 2018.

[18] J. Saxton, *A High-Injury Network for Atlanta: How are severe and fatal injury crashes concentrated on Atlanta's streets?,* Georgia Institute of Technology, 2018.

[19] San Francisco Department of Public Health, "Vision Zero High Injury Network: 2017 Update - A Methodology for San Francisco, CA," 2017.

[20] City of Los Angeles, "High Injury Network - Development and Methodology," 2016.

[21] F. R. Proulx and R. L. Sanders, "High Injury Networks - Why, When, and How to Use Them: A Case Study," in *TRB 98th Annual Meeting,* Washington DC, 2019.

[22] K. Fitzpatrick, R. Avelar and S. Turner, "Guidebook on Identification of High Pedestrian Crash Locations," USDOT, Washington D.C., 2018.

[23] L. Thomas et al., "Systemic Pedestrian Safety Analysis," NCHRP, Washington DC, 2018.

[24] L. Miranda-Moreno, P. Morency and A. El-Geneidy, "The link between built environment, pedestrian activity, and pedestrian--vehicle crashes," *Accident Analysis and Prevention,* vol. 43, pp. 1624-1634, 2011.

[25] C. Y. Yu, "Built environmental designs in promoting pedestrian safety," *Sustainability,* vol. 7, no. 7, pp. 9444-9460, 2015.

[26] U. R. R. Manepalli and G. H. Bham, "Identification of crash-contributing factors: effects of spatial autocorrelation and sample data size," *Transportation Research Record,* vol. 2386, pp. 179-188, 2013.

[27] H. A. Aziz, S. V. Ukkusuri and S. Hasan, "Exploring the determinants of pedestrian--vehicle crash severity in New York City," *Accident Analysis & Prevention,* vol. 50, pp. 1298-1309, 2013.

[28] R. J. Schneider et al., "Association between roadway intersection characteristics and pedestrian crash risk in Alameda County, California," *Transportation Research Record,* vol. 2198, pp. 41-51, 2010.

[29] P. J. Ossenbruggen, J. Pendharkar and J. Ivan, "Roadway safety in rural and small urbanized areas," *Accident Analysis & Prevention,* vol. 33, no. 4, pp. 485-498, 2001.

[30] A. Osama and T. Sayed, "Evaluating the impact of connectivity, continuity, and topography of sidewalk network on pedestrian safety," *Accident Analysis & Prevention,* vol. 107, pp. 117-125, 2017.

[31] C. Harvey and L. Aultman-Hall, "Urban streetscape design and crash severity," *Transportation Research Record,* vol. 2500, no. 1, pp. 1-8, 2015.

[32] L. Thomas et al., "Changing the Future? Development and Application of Pedestrian Safety Performance Functions to Prioritize Locations in Seattle, Washington," *Transportation Research Record,* vol. 2659, pp. 212-223, 2017.

[33] K. J. Clifton, C. V. Burnier and G. Akar, "Severity of injury resulting from pedestrian-vehicle crashes: What can we learn from examining the built environment?," *Transportation Research Part D: Transport and Environment,* vol. 14, no. 6, pp. 425-436, 2009.

[34] H. Coleman and K. Mizenko, "Pedestrian and Bicyclist Data Analysis: Traffic Safety Facts," NHTSA, 2018.

[35] A. Montella et al., "Data mining techniques for exploratory analysis of pedestrian crashes," *Transportation research record,* vol. 2237, pp. 107-116, 2011.

[36] S. Turner et al., "Syntehsis of methods for estimating pedestrian and bicyclist exposure to risk at areawide levels and on specific transportation facilities," FHWA, 2017.

[37] C. Lyon and B. Persaud, "Pedestrian collision prediction models for urban intersections," *Transportation Research Record,* vol. 1818, pp. 102-107, 2002.

[38] R Core Team, *R: A Language and Environment for Statistical Computing,* Vienna, Austria: R Foundation for Statistical Computing, 2021.

[39] Stan Development Team, *RStan: the R interface to Stan,* 2020.

[40] W. Chang et al., *shiny: Web Application Framework for R,* 2021.

[41] H. Schneider, "Louisiana Crash Costs," Louisiana Highway Safety Research Group, 2020.

[42] L. Blincoe et al., "The Economic and Societal Impact of Motor Vehicle Crashes," NHTSA, 2010.

[43] T. Harmon, G. Bahar and F. Gross, "Crash Costs for Highway Safety Analysis," FHWA, 2018.