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# Suppressed child pedestrian and bicycle trips as an indicator of safety: Adopting a proactive safety approach

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ABSTRACT

Traditional pedestrian and bicyclist safety analyses typically examine crashes, injuries, or fatalities. However, this reactive approach only accounts for the places where people are currently walking or biking and those that are doing so. Would a proactive approach – examining areas where pedestrian and bicyclist activity is being suppressed because of safety concerns – illuminate other previously neglected safety issues?

The goal of this work is to compare results from reactive and proactive pedestrian and bicyclist safety analyses. To accomplish this, we focus on child pedestrians and bicyclists in Denver, Colorado because of the structured characteristics of their travel behavior regarding trips to school. We complete a reactive crash cluster analysis and a proactive safety analysis that is based on trip suppression due to traffic safety concerns. A parental perception survey informs the mode choice model we create for the proactive safety analysis.

Findings suggest that reactive approaches identify downtown Denver and major corridors as unsafe, while the proactive analysis also identifies neighborhoods in west, east, and northeast Denver. Due to an absence of crashes, the majority of these areas would not normally be considered unsafe for pedestrians and bicyclists based on conventional reactive approaches. The fact that they are perceived as unsafe may be limiting usage and thereby limiting the number of crashes. In order to improve safety where children are currently walking and bicycling – as well as where they want to walk or bike – traditional analyses would benefit from augmentation by such a proactive safety approach.

## 1. Introduction

Researchers traditionally analyze crashes, injuries, or fatalities when examining traffic safety of walking and bicycling trips (Federal Highway Administration, 2006; Zegeer et al., 2010). However, the only people that are accounted for in this reactive approach to safety are those who are already walking or biking – the people who have decided that those activities are safe enough to pursue. What about the people who – because of traffic safety concerns – have decided to not walk or bike in the first place? Furthermore, the only locations that are identified in reactive approaches are the locations that have pedestrians and bicyclists present. What about the places where people have decided not to walk or bike? How would we proactively identify these places as unsafe before a crash occurs or even before any walking or biking occurs?

Past research has investigated how perceptions of traffic safety impact the choice to walk or bike (Cho et al., 2009; Schneider

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et al., 2003; Nevelsteen et al., 2012). We propose building upon this work by quantifying walking and bicycling trip suppression due to traffic safety concerns and using active transportation trip suppression as an indicator of traffic safety risk. If high levels of pedestrian and bicycle trips are being suppressed due to traffic safety concerns, this suggests that there are traffic safety issues present, regardless of whether crashes are occurring. We then compare results from our proactive safety analysis to results from a traditional reactive analysis.

To accomplish these objectives, we reactively and proactively analyze the safety of children's walking and biking trips to and from school in Denver, Colorado. Children are some of the most vulnerable road users and depend on walking and biking if they wish to have independent mobility. Their trips to school are also highly structured, making this an ideal group to study. For the reactive approach, we complete a crash cluster analysis specific to child pedestrians and bicyclists. For the proactive approach, we weigh shortest path distances with suppression proportions from a parental perceptions survey to derive the level of child school trip suppression associated with traffic safety concerns. Finally, we compare results from this proactive analysis to results from the traditional reactive crash analysis. If our goals include promoting walking and biking activity instead of simply reducing existing pedestrian and bicycle crashes, such a proactive safety analysis may represent an important new perspective on pedestrian and bicyclist safety.

## 2. Theory

Traditional safety analyses rely on crashes, injuries, or fatalities to identify unsafe roadways (Transportation Research Board, 2001; Waldheim et al., 2015). This approach is utilized for safety studies of vehicles as well as for pedestrians and bicyclists (Federal Highway Administration, 2006; Zegeer et al., 2010). Ideally, these crash-based safety analyses account for exposure – a pedestrian or bicyclist's proximity to potentially harmful situations involving motor vehicles – in the form of distance or time traveled, user counts, times crossing a street, or the product of pedestrian or bicyclist and vehicle volumes (Molino et al., 2012). However, the lack of reliable pedestrian and bicyclist exposure data makes such comparisons difficult (Turner et al., 2017). In the absence of appropriate exposure data, cluster analyses of crashes are a common approach used to identify areas of safety concern (Blackburn et al., 2017).

The four pedestrian and bicyclist safety analyses for Denver, Colorado that were most recently completed by local and regional transportation agencies consisted of traditional crash-based analyses that did not account for exposure (Denver Public Works (DPW), 2016; DPW, 2017; Denver Regional Council of Governments (DRCOG), 2012; DRCOG, 2017). While such a focus on crashes can allow for the successful identification and reduction of those crashes, it is by nature a reactive approach that requires a crash to occur before any safety issues can be identified. Because a pedestrian or bicyclist crash cannot take place unless there is a pedestrian or bicyclist present, this conventional approach only accounts for people who are currently walking or biking and the places where they are doing so.

A proactive approach to safety is one that identifies areas that are likely to experience crashes before those crashes occur. It could also be an approach that identifies areas where safety concerns have caused low levels of pedestrian and bicyclist activity and have therefore effectively hidden safety issues from the objective eye. For instance, proactive approaches can be effective when exposure levels – and therefore crash levels – are so low that traditional indicators do not provide an accurate representation of risk (Cho et al., 2009; Schneider et al., 2003). Perceptions of safety have been shown to correlate with exposure levels and may therefore proactively indicate safety issues (Noland, 1995; Pucher et al., 2010). In other words, while a road perceived as unsafe may suppress walking and biking trips, and therefore reduce or preclude pedestrian and bicycle crashes, these same negative safety perceptions can be used as an indicator that safety issues – albeit hidden from conventional, objective analyses – are present.

Past researchers have taken several approaches when using perceptions of safety to proactively identify pedestrian and bicyclist safety issues. An early attempt surveyed pedestrians and drivers on the campus of the University of North Carolina at Chapel Hill, asking them to identify locations that posed safety issues to pedestrians (Schneider et al., 2003). When the researchers compared these subjective perceptions to objective outcomes, it became apparent that there were areas perceived as unsafe that had no crashes occurring. Researchers determined that, while these areas were otherwise desirable to pedestrians, the perception of these areas as 'accidents waiting to happen' was reducing levels of exposure. While these results provide a theoretical foundation for our work, the method of identifying unique hotspots is not scalable. In other words, because the perceptions were not tied to specific characteristics of the built environment, the survey would need to be re-administered for every new area that may be studied in the future. We seek a methodology that can be generalized and applied to other areas.

Cho et al. (2009) improved upon this scalability issue by creating a risk estimate based on built environment characteristics such as land use mix and street connectivity. They found that increased perceptions of risk for pedestrians and bicyclists reduced crash rates because of decreased usage. However, the methods did not account for street-level risk factors such as roadway width, vehicle speeds, and vehicle volumes, which could have an impact on behavior. This approach and its results have relatively limited implications for built environment improvements as road network connectivity and land use mixes are not as easily addressed as vehicle volumes, vehicle speeds, or sidewalk gaps.

Nevelsteen et al. (2012) built upon these trip suppression studies by examining the relationship between perceptions of street-level risk factors and pedestrian and bicyclist trip allowance for children traveling to school. However, the researchers only examined two factors: the presence of pedestrian and bicycle facilities and vehicle speeds. Furthermore, the study was performed in a Belgian context that reports 40% of 11 and 12-year olds cycling to school – a transportation culture that is vastly different from much of the world.

All of the studies examining safety perceptions showed that perceptions of safety and trip suppression differ from objective safety outcomes such as crashes. Specifically, Cho et al. (2009) and Schneider et al. (2003) found that perceptions of unsafe conditions lowered use and therefore exposure, which improved objective safety outcomes, thereby hiding the safety issues. However, these past proactive analyses – while providing a strong foundation for the research at hand – were either focused on small areas, included few roadway variables, or were in unfamiliar contexts. We therefore create a new proactive model that quantifies trip suppression for children's trips to and from school with additional roadway risk factors and then compare results to those from more conventional reactive crash-based analyses. We hypothesize that the reactive and proactive analyses will illuminate different safety concerns, thereby successfully complementing one another.

## 3. Data

We utilized the City and County of Denver for our analysis. Denver has a population of 663,303 according to the 2016 American Community Survey. Because Denver has detailed crash data available and high enough population, pedestrian, and bicyclist levels to obtain significant samples, it was an ideal location for our study.

While there are suitable levels of walking and biking, there are also pedestrian and bicyclist safety issues present. According to DPW reports and data from DRCOG – the local metropolitan planning organization – there were 1508 pedestrians and 1083 bicyclists hit by motor vehicles in Denver between 2011 and 2014 (DPW, 2017). These collisions resulted in injuries for 918 pedestrians and 791 bicyclists, with 72 pedestrians and seven bicyclists killed (DPW, 2016; DPW, 2017).

### 3.1. Reactive analysis

We performed our own crash cluster analysis of pedestrian and bicyclist crashes in Denver that was specific to children. Crashes were pulled from DRCOG's Regional Data Catalog in GIS point format for the years 2010–2014. We included any crash involving a pedestrian or bicyclist under the age of 14 in our analysis in order to match the proactive analysis. Similar to the agency-produced reports, we did not account for exposure in our spatial analysis as reliable counts of child pedestrians and bicyclists were not available. We accounted for exposure with population counts for our numerical analysis.

### 3.2. Proactive analysis

The goal of the proactive safety analysis was to quantify the level of child pedestrian and bicyclist trip suppression caused by traffic safety concerns and utilize that as an indicator of safety. There were two aspects of the proactive safety analysis: (1) suppression rates based on survey-derived parental perceptions of roadway characteristics; and (2) routes to school based on a GIS closest facility network analysis.

For the suppression rates, we administered a survey to parents of children enrolled in pre-kindergarten through 8th grade in Denver, Colorado, asking them which roadway characteristics they would allow their child to walk or bike on. Roadway characteristics included number of lanes, posted vehicle speed limits, vehicle volumes, and the presence of sidewalks and bike lanes. We will expand further on the survey methods in Section 4. For a more exhaustive review, please refer to Ferenchak and Marshall (2019).

To derive the shortest path distances to schools, we utilized a closest facility GIS network analysis with child home locations as origins and schools as destinations. We approximated child home locations on the block group level by creating a random point for each child based on population numbers from the 2015 American Community Survey. The National Historical Geographic Information System (NHGIS) provided us with this population dataset (Manson et al., 2017). We clustered origin points according to residential building footprints provided by the City and County of Denver's Open Data Catalog in polygon shapefile format. School destinations were in point shapefile format from DRCOG's Regional Data Catalog. The analysis considered only public elementary and middle schools.

Data for Denver's street network came from the Denver Open Data Catalog in GIS polyline shapefile format. This layer included posted speed limits and the number of lanes for each road segment. We utilized vehicle volumes provided by DRCOG, considering any roadway with more than 1000 vehicles per day as high volume (Cornell Local Roads Program, 2014). We noted the presence of sidewalks based on the DRCOG Regional Data Catalog's GIS sidewalk layer, which was provided in polyline shapefile format. We accounted for bike lanes based on their location per Google Maps, satellite imagery, and Google Street View and accounted for the off-road multi-use path network based on a layer provided by the Denver Open Data Catalog.

## 4. Methods

The work is broken into reactive and proactive analyses, the results of which are then compared (Fig. 1).

### 4.1. Reactive analysis

The Optimized Hotspot Analysis tool in Esri's ArcMap allowed us to identify statistically significant clusters of child pedestrian and bicyclist crashes. The tool functions to identify both hotspots and cold spots in incident data. When inputting the data, we considered each crash point as a single equally-weighted incident. The tool automatically aggregates all incidents found to be clustered into a mean centroid point and outputs the Getis-Ord Gi* statistic in the form of a confidence level bin for each identified cluster. We utilized clusters that were in the 95% confidence bin (two standard deviations for normally-distributed data) and had at least three crashes. Once these aggregated clusters were identified, we returned to the original crash point layer and assigned each crash to its appropriate cluster.

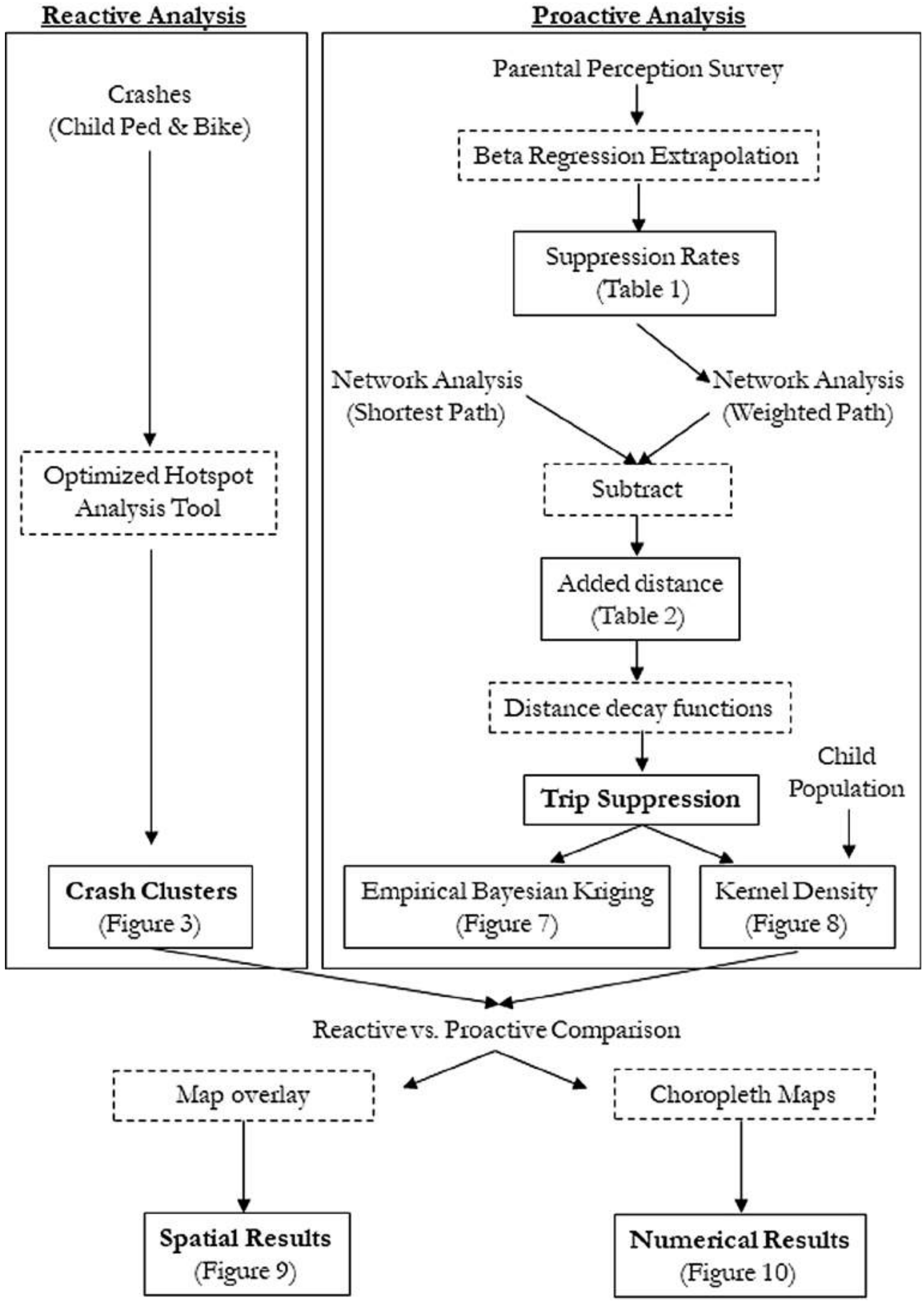


**Fig. 1.** Methods overview.

### 4.2. Proactive analysis

We first administered a parental survey to quantify how perceptions of roadway characteristics influence suppression of children's pedestrian and bicycle trips. We then completed a GIS network analysis to find the shortest path distance between the estimated home location of each child in Denver and their closest school. We next applied the trip suppression rates to the road network and ran the network analysis once again. This allowed us to measure the additional walking or biking distance required to avoid traffic safety issues. Finally, we used distance decay functions to estimate the levels of trip suppression.

A survey of parents of children in elementary and middle school provided us with the proportion of children's pedestrian and bicyclist trips that are suppressed because of safety concerns. The survey excluded parents of high school students because those students have more independence than younger students and would be more likely to drive themselves or carpool with a friend. The survey was offered exclusively online and was marketed through newsletters, fliers, and social media by Denver Public Schools, the City and County of Denver, parent-teacher organizations, and local advocacy groups. The survey was open in 2017 during the month of October in both English and Spanish. The 1298 survey respondents provided us with 924 complete responses accounting for 1331 children.

Parents first provided information regarding child age, gender, and physical activity levels. The survey then presented parents with a variety of scenarios consisting of varying roadway design characteristics and asked whether they would allow their child to walk or bike to school on each roadway (Fig. 2). Each scenario included a corresponding picture from a road in Denver. Scenarios contained consistent aesthetics and residential land use contexts. Parents were able to answer "No", "Yes, with trusted adult supervision", or "Yes, without adult supervision". Each survey included five randomly selected walking questions and five randomly selected bicycling questions from a pool of twenty walking questions and twenty bicycling questions. Roadway design characteristics included number of lanes (2, 3, or 4 lanes), posted speed limits (25 mph, 35 mph, or 45 mph), the presence of sidewalks and bike lanes (none or on one or both sides of the road), and vehicle volumes (low or high volumes). Parent responses were converted into proportions of disallowance (also referred to as the suppression rate) for each of the forty roadway scenarios. We calculated suppression rates by dividing the total number of responses by the number of parents responding "No." Therefore, for the sake of this paper, we treated "Yes, with trusted adult supervision" and "Yes, without adult supervision" responses the same.

Since the number of roadway scenarios in Denver exceeded the number of scenarios that we could feasibly include on the survey, we developed a beta regression general linear model (GLM) to derive a suppression rate for each roadway scenario in Denver (Table 1). The betareg package in R provided us with the ability to create this beta regression with a logit link function. The beta regression GLM is superior to a standard linear regression when the dependent variable is in the form of a proportion bounded between zero and one and when – as was present in our data – normality is weak (Hayter, 2007). We formed the beta regression GLM by taking the twenty walking scenarios and twenty biking scenarios included in the survey and coding the four predictor variables as dummy variables. This allowed for standardization of the regression results. The 25 mph and two-lane variables were removed from the model to avoid multi-collinearity. We designated the outcome variable as the proportion of parents that would not allow their children to use each roadway scenario.

With these beta regression results, we then derived the corresponding suppression rate for each Denver roadway scenario that was not featured in the survey. Road attributes found throughout Denver included speeds of 15 mph, 25 mph, 30 mph, 35 mph, 40 mph, 45 mph, and 55 mph, number of lanes from one to nine, non-motorized facilities on zero, one, or two sides of the road, and low or high vehicle volumes. There were 138 roadway scenarios for walking and 78 scenarios for biking.

We then derived the level of trip suppression for each child. We accomplished this by determining the shortest path distance between each child's estimated home location and their closest school and then computing how much distance would be added to those trips if the children avoided roads perceived as unsafe. To avoid edge issues, we included children outside of Denver if their closest school was located in Denver. Because of privacy issues, we approximated the location of children's homes on the block group level by creating one random point for each child living in each block group. We clustered random points to residential building footprints so that trips would originate in realistic patterns. While the assumption that each child will attend their closest school is known to be faulty because of the Colorado Open Enrollment program that allows children to attend schools other than their originally assigned neighborhood school, privacy issues precluded us from knowing which school each child actually attends. Even if these children were not attending their closest school, the areas near their homes would be where we would expect the majority of children's trips, assuming that many children's walking and biking trips originate from their home.

After determining the shortest path distance from each child's estimated home to their closest school, we then reran the network analysis with each road segment weighted according to safety-perception-based suppression rates. In this scenario, routes became a balance of travel costs associated with distance and safety perceptions. We therefore needed to standardize these two variables. Distance decay functions allowed us to standardize the variables in a probabilistic manner (Iacono et al., 2008). Distance decay functions are inverse power functions that use distance or time as a proxy for travel costs. Those used in our survey were developed based on data from travel surveys, joint-use facility user surveys, and a Non-Motorized Pilot Program (NMPP) survey from the Twin Cities region (Iacono et al., 2008). The functions were specific to children walking and biking to school. The distance decay function for walking to school had a dependent variable of percent of school and school-based trips made by walking and an independent variable of travel time in minutes (Eq. (1)). Because we needed to standardize the variables into a distance so that we could perform a closest facility analysis, we used an assumption of 25 min per mile for pedestrian speed (a rough conversion of the standard 3.5 feet per second used in the Manual on Uniform Traffic Control Devices).

$$y = 0.523e^{-0.10x} \tag{1}$$

where:

y = percent of school or school-related trips made by walking
x = travel time (min)

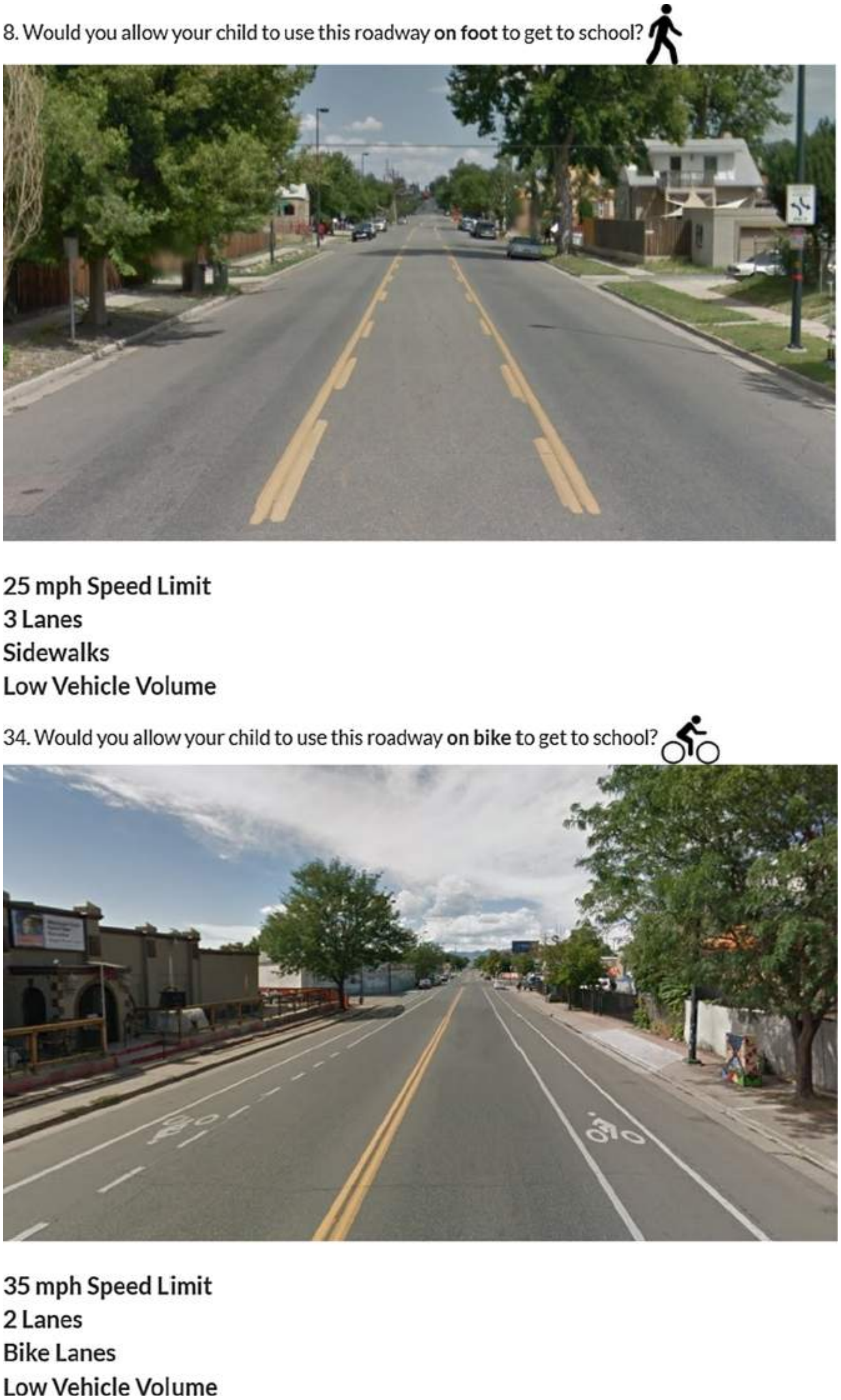


**Fig. 2.** Example of survey questions.

**Table 1**
Predictors of the proportion of parents who would not allow their child to walk or bicycle.

| | | Walk $R^2 = 0.977; n = 20$ | Bike $R^2 = 0.9509; n = 20$ |
|---|---|---|---|
| Intercept | | $-0.260^{*}$ | $-0.703^{***}$ |
| Speed | 35 mph | $0.995^{***}$ | $0.644^{***}$ |
| | 45 mph | $1.868^{***}$ | $0.901^{***}$ |
| Lanes | 3 lanes | $0.495^{***}$ | $0.618^{***}$ |
| | 4 lanes | $0.597^{***}$ | $1.166^{***}$ |
| Facilities | | $-2.584^{***}$ | $-0.819^{***}$ |
| Volume | | $0.770^{***}$ | $1.111^{***}$ |

$^{*}p < 0.01$.
$^{**}p < 0.05$.
$^{***}p < 0.001$.

The distance decay function for biking to school (Eq. (2)) had a dependent variable of percent of school and school-based trips made by biking and an independent variable of travel distance in kilometers. We converted the function to feet to coincide with the foot-based network analysis. We also transformed both distance decay functions so that a value of 100% of trips correlated with a distance of zero. This avoided any negative distance outcomes, which would not have been acceptable in the network analysis.

$$y = 0.4651e^{-0.1236x} \quad (2)$$

where:

y = percent school or school-related trips made by biking
x = distance (km)

Because the GIS network analysis was based on trip distance, we used the distance decay functions to translate safety perceptions into distance values, and then used those distance values as our weights. This method is justified because distance decay functions can be interpreted as both measuring the impedance to travel through a network as well as willingness of individuals to travel various distances to access opportunities (Iacono et al., 2008). As an example of this method, a road segment with a pedestrian disallowance rate of 25% was given a weight of approximately 711 feet while a segment with a pedestrian disallowance rate of 95% was given a weight of approximately 7400 feet. We applied these additional distances as added-cost barriers in point format. We assigned the point barriers at the midpoint of each segment. Therefore, when we ran the weighted network analysis, we accounted for both distance and perceptions in units of feet. In this way, model agents were able to decide between a short, unsafe route and a long, safe route.

Since roadways had different suppression rates for walking and biking, we ran this weighted network analysis twice, once for each mode. We then determined the difference between the original shortest path distance and the weighted distance. The distance decay functions allowed us to derive a probabilistic estimate of trip suppression for each child. By inputting into our distance decay functions the additional distance added to each trip in the weighted network analysis, we converted the additional distance to a percentage of suppression. In other words, if a child's walking trip increased by 711 feet when we accounted for safety perceptions, that child's trip was considered 25% suppressed. If a child's trip increased by 7400 feet, that child's trip was considered 95% suppressed.

Once we estimated levels of suppression for each trip, we interpolated suppression values for all of Denver through an Empirical Bayesian kriging (EBK) tool in GIS. EBK uses known point values to interpolate values for cells in a raster layer. EBK is superior to standard kriging approaches because it accounts for uncertainty introduced with the estimation of the semivariogram. We used a power semivariogram with no transformation. This analysis allowed us to estimate levels of trip suppression while not yet accounting for the number of possible users.

We were then interested in combining levels of trip suppression with the number of possible users. In other words, one neighborhood might have high levels of trip suppression but only one possible user, while another neighborhood might have slightly less trip suppression but many possible users. Kernel density analysis in GIS enabled us to simultaneously account for levels suppression and users by estimating a magnitude-per-unit area for cells in a raster layer. Child points were the base layer and trip suppression rates (as proportions) were the population variable. We employed a planar method.

This kernel density analysis also allowed us to perform a spatial comparison of our reactive and proactive analyses by overlaying child pedestrian and bicyclist crash clusters on top of our kernel density outputs in GIS. We then confirmed these spatial observations with numerical choropleth maps. We performed the numerical choropleth analysis on the neighborhood level by deriving the number of crashes per 1000 child residents for each neighborhood and the average level of trip suppression for each neighborhood. We defined data classes with natural breaks (Jenks). A buffer of fifty feet allowed us to avoid edge issues.

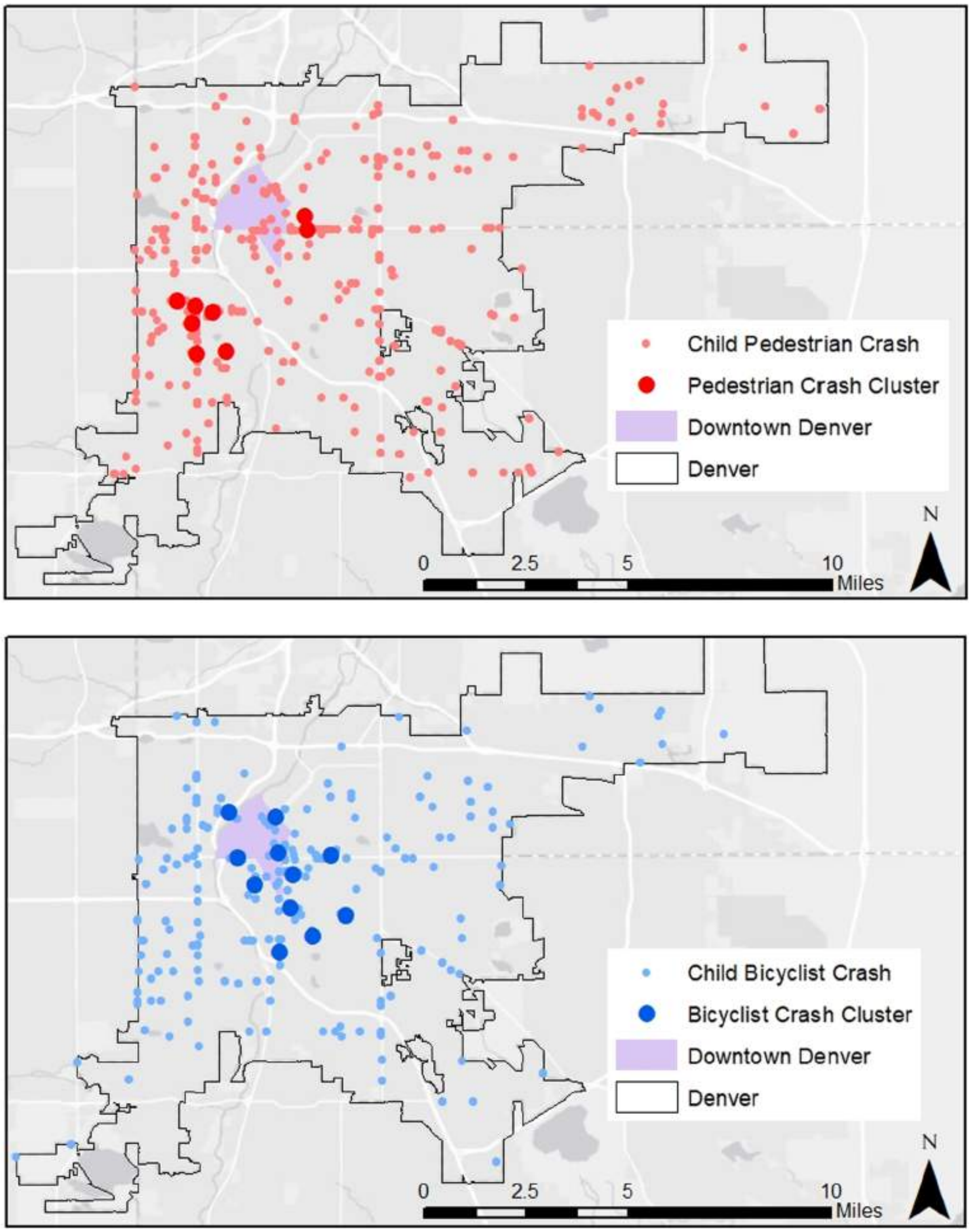


**Fig. 3.** Child crash clusters for pedestrians (above) and bicyclist (below), 2010–2014.
*Data Source:* DRCOG Regional Data Catalog.

## 5. Results

### 5.1. Reactive analysis

Between 2010 and 2014, 342 child pedestrian crashes and 208 child bicyclist crashes occurred in Denver. For the 342 child pedestrian crashes, there were fifty-two clusters identified consisting of a total of 219 crashes. Of these fifty-two identified clusters, eight clusters were significant at 95% confidence and consisted of at least three crashes. These eight clusters contained a total of 31 child pedestrian crashes. The largest cluster used in the analysis had six crashes, and the smallest had three. For the 208 child bicyclist crashes, there were thirty-two clusters identified consisting of a total of 150 crashes. Of these thirty-two identified clusters, eleven clusters were significant at 95% confidence and consisted of at least three crashes. These eleven clusters contained a total of 67 child bicyclist crashes. The largest cluster used in the analysis had twelve crashes and the smallest had three.

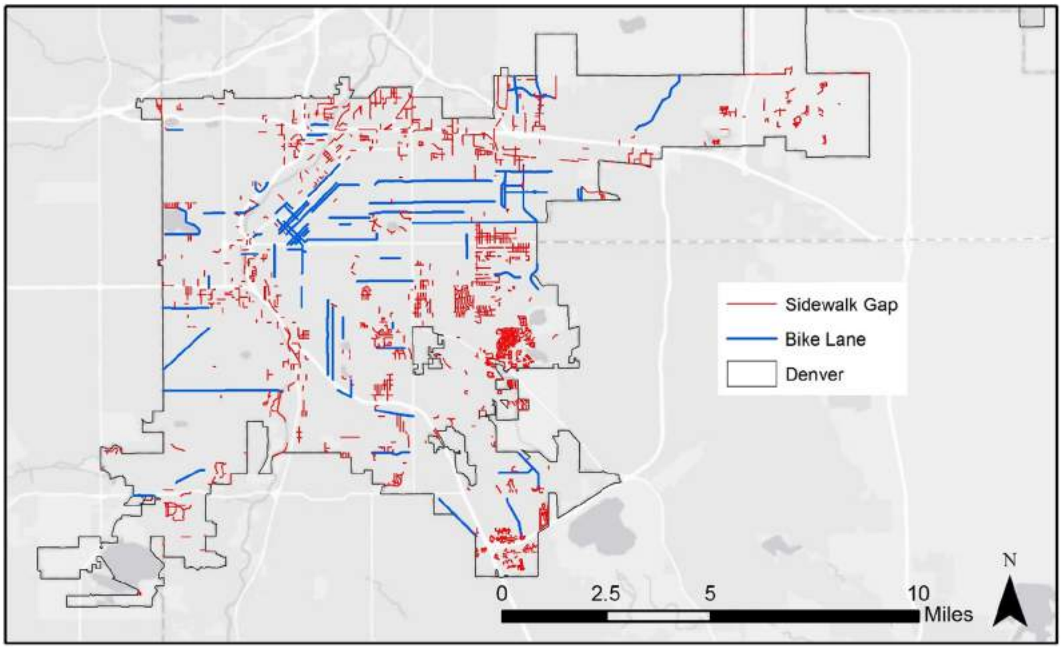


**Fig. 4.** Location of pertinent roadway characteristics in Denver.
*Data Source:* Denver Data Catalog and DRCOG Regional Data Catalog.

Pedestrian crash clusters are focused in an area around South Federal Boulevard and just outside of downtown Denver (Fig. 3). The bicyclist crash clusters are primarily focused in the area proximate to and south of downtown Denver (Fig. 3). The rest of the residential neighborhoods that largely comprise Denver have few identified clusters. The majority of un-clustered crashes occur near downtown and in west Denver as well.

### 5.2. Proactive analysis

Based on survey results from parents, the most important roadway characteristic in terms of walking trip suppression was the presence of sidewalks (Table 1). There are limited sidewalk gaps in central Denver but larger concentrations of sidewalk gaps present in east and north Denver (Fig. 4). The most important roadway characteristic in terms of bicycling trip suppression was vehicle volumes (approximately equivalent to adding two additional lanes to a two-lane road) with the presence of bike lanes being slightly less important (Table 1). Wide, high volume roadways are found throughout Denver while bike lanes are primarily located downtown and in an east-west orientation to the northeast of downtown Denver (Fig. 4).

There were 136,138 children included in the proactive analysis with 112,648 children living in Denver and 23,490 children living in municipalities directly bordering Denver. The highest concentrations of children are found in the residential areas in west and northeast Denver (Fig. 5). We included 217 public elementary and middle schools – both inside and outside Denver – in the analysis (Fig. 5).

Within GIS, the network analysis tool was able to derive a pathway to each child's closest school. Of the children considered in the proactive analysis, 56.8% of children had a shortest path of 0.5 miles or less to their closest school (via network distance as opposed to Euclidian distance), and 93.1% of children had a shortest path of one mile or less (Fig. 6).

Next, we weighted the network analysis with trip suppression rates and re-ran the analysis for both walking and bicycling trips. Trip lengths increased for both walking and biking trips once barriers were added into the network analysis (Table 2). Trip lengths for bicyclists increased more, reflecting the fact that parents found bicycling less safe than walking. The average shortest path distance for pedestrians and bicyclists was approximately one-half mile. Average trip lengths increased by 294 feet for walking and 481 feet for biking after barriers were added to the network analysis. However, those increases were averages for the entire city and spatial clustering was present in parts of Denver (Ferenchak & Marshall, 2019).

Empirical Bayesian kriging shows that clustering of elevated levels of trip suppression are found throughout several neighborhoods in Denver (Fig. 7). These results interpolate and extrapolate suppression levels without accounting for population concentrations. We resampled the raster layer with cubic convolution.

We then accounted for population concentrations in our suppression analysis. Kernel density results suggest that there are suppression-population concentrations in west, east, and northeast Denver, but few concentrations in central Denver (Fig. 8). These trends are most likely related to the lower concentrations of children and fewer perceived safety issues (there are few sidewalk gaps

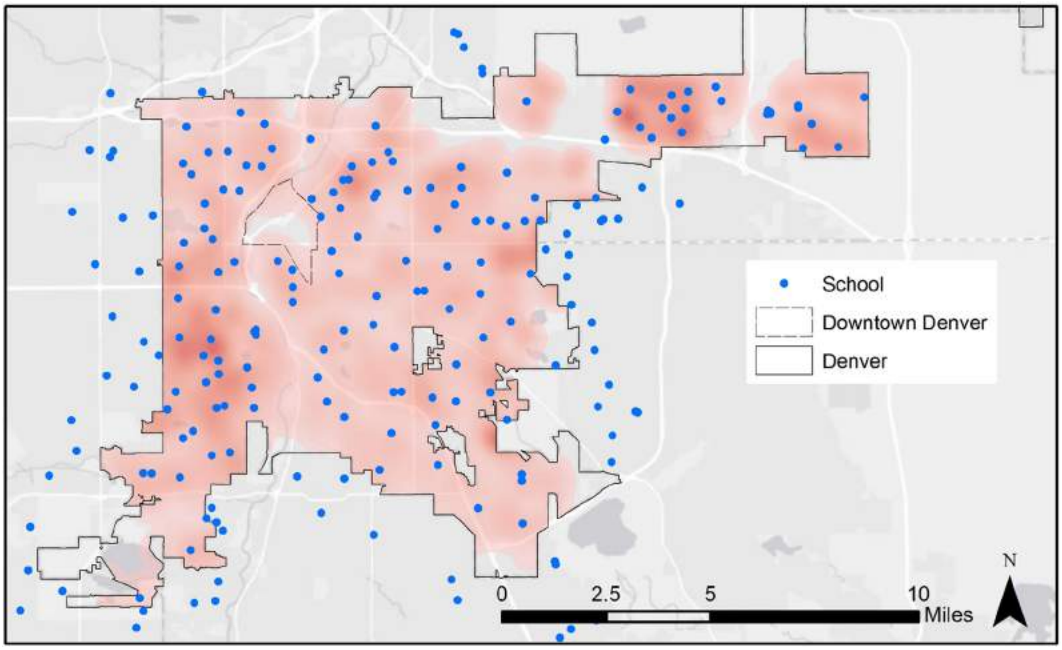


**Fig. 5.** Child population concentrations (red = higher concentration) and school locations in Denver. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
*Data Source:* U.S. Census Bureau.

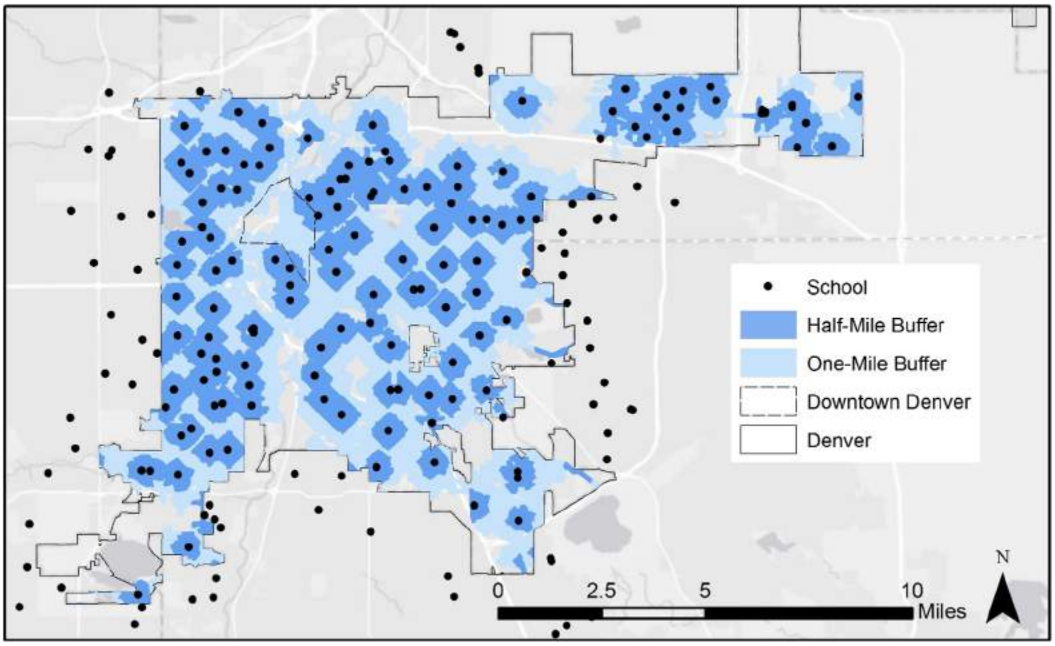


**Fig. 6.** Half-mile (walkshed) and one-mile (bikeshed) network buffers around schools in Denver.

and many bike lanes) found in central Denver. The large concentration of walking suppression in east Denver coincides with high concentrations of children and sidewalk gaps while concentrations in west Denver primarily correspond with Federal Boulevard, a wide, busy, and higher-speed road (Fig. 8). The concentration in northeast Denver coincides with a neighborhood that includes a curvilinear tributary network, where all trips are forced to funnel onto larger, higher-volume roads.

**Table 2**
Child pedestrian and bicycling trip lengths in feet.

| | Walk | Bike |
|---|---|---|
| **Shortest Path** | | |
| Shortest | 5.2 | 5.2 |
| Average | 2681.1 | 2681.1 |
| Longest | 9710.9 | 9710.9 |
| Std. Dev. | 1465.6 | 1465.6 |
| **Weighted Path** | | |
| Shortest | 5.2 | 5.2 |
| Average | 2974.6 | 3162.3 |
| Longest | 13,354.9 | 14,917.4 |
| Std. Dev. | 1792.7 | 2029.3 |

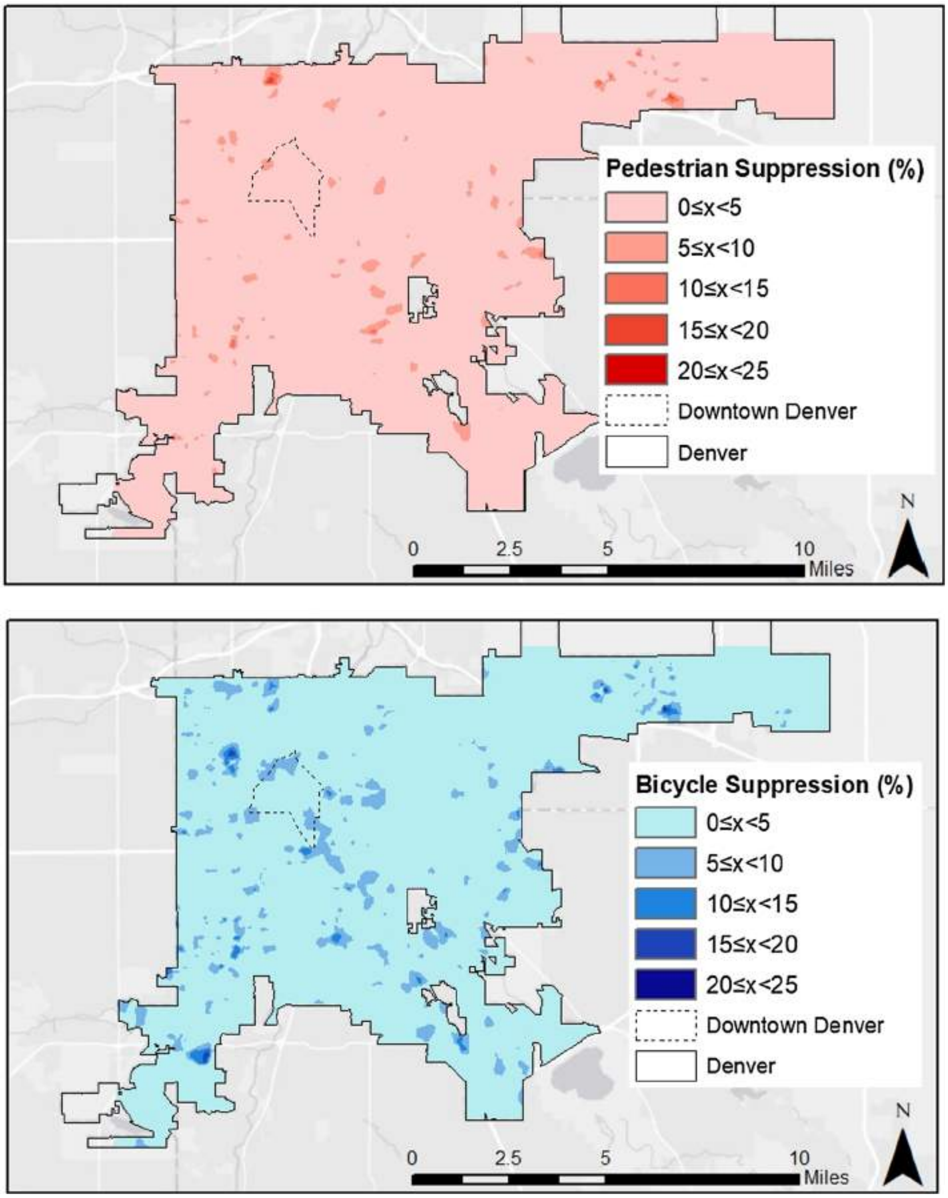


**Fig. 7.** Trip suppression for child pedestrian (above) and bicyclist (below) trips.

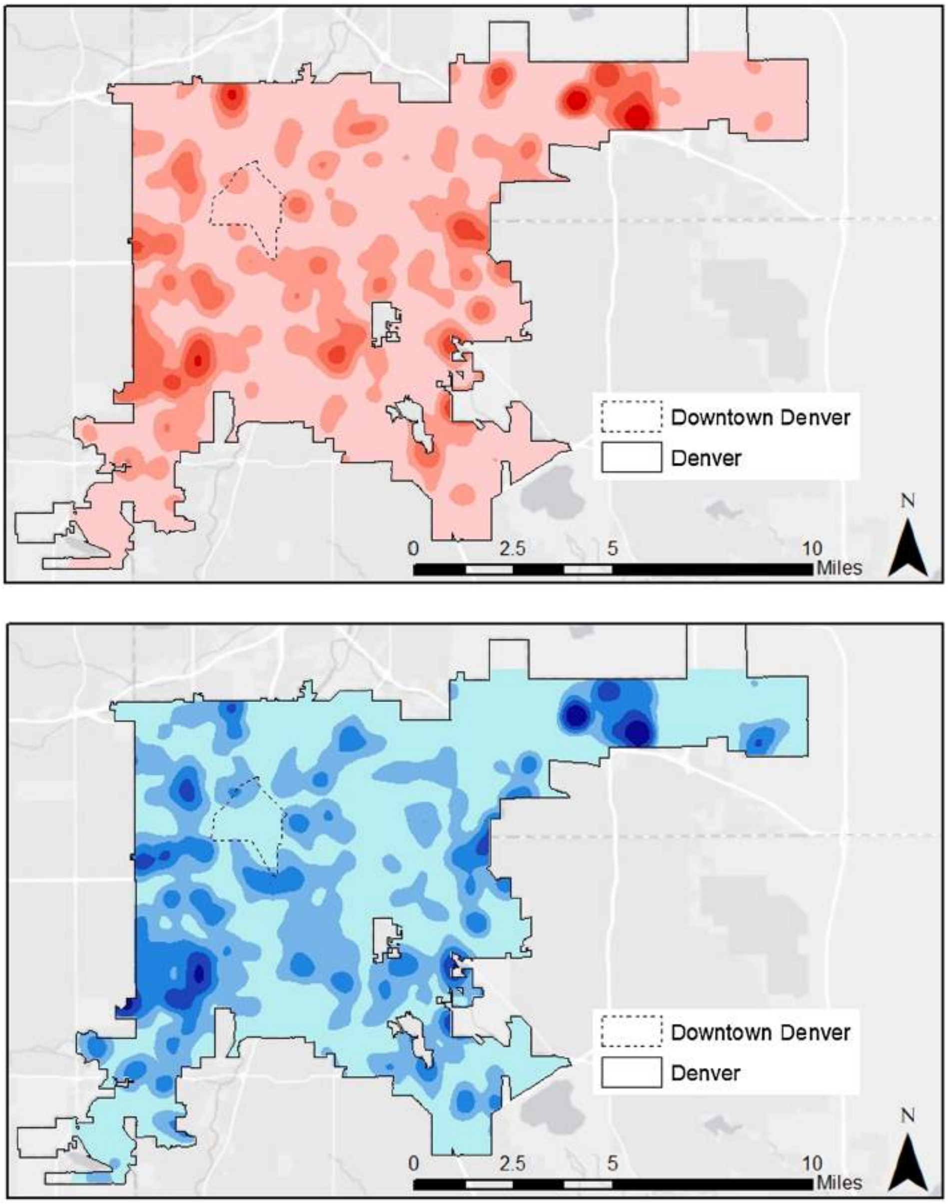


**Fig. 8.** Trip suppression weighted by child populations (dark = higher concentration) for child pedestrian (above) and bicyclist (below) trips.

### 5.3. Comparison

The reactive pedestrian and bicyclist safety analyses identify areas near downtown and central Denver as well as S. Federal Boulevard (for pedestrians) as the areas of most concern. Safety issues in these areas have manifested in the form of high levels of crashes. However, Fig. 9 shows that – in addition to the proactive pedestrian analysis identifying S. Federal Boulevard – the proactive analyses alternatively identify areas in east, northeast, and west Denver as having perceived traffic safety issues. These safety concerns may be hidden by a lack of non-motorized activity (despite the high concentrations of children) resulting from trip suppression. This trip suppression precludes crashes from occurring in the first place and, therefore, from being visible in a conventional reactive analysis.

We supplemented the spatial analysis with numerical analysis in the form of choropleth maps (Fig. 10). Numerical results confirm the spatial findings; crash rates for child pedestrians and bicyclists are highest around downtown while suppression is found dispersed throughout the city. The coarse-grained nature of the neighborhood analysis precludes strong geographic trends in suppression because – as we saw in the spatial analysis – suppression can be highly localized. That being said, the proactive analysis on the neighborhood level does generally identify issues in northeast and east Denver as well as near South Federal Boulevard, just as with the spatial analysis.

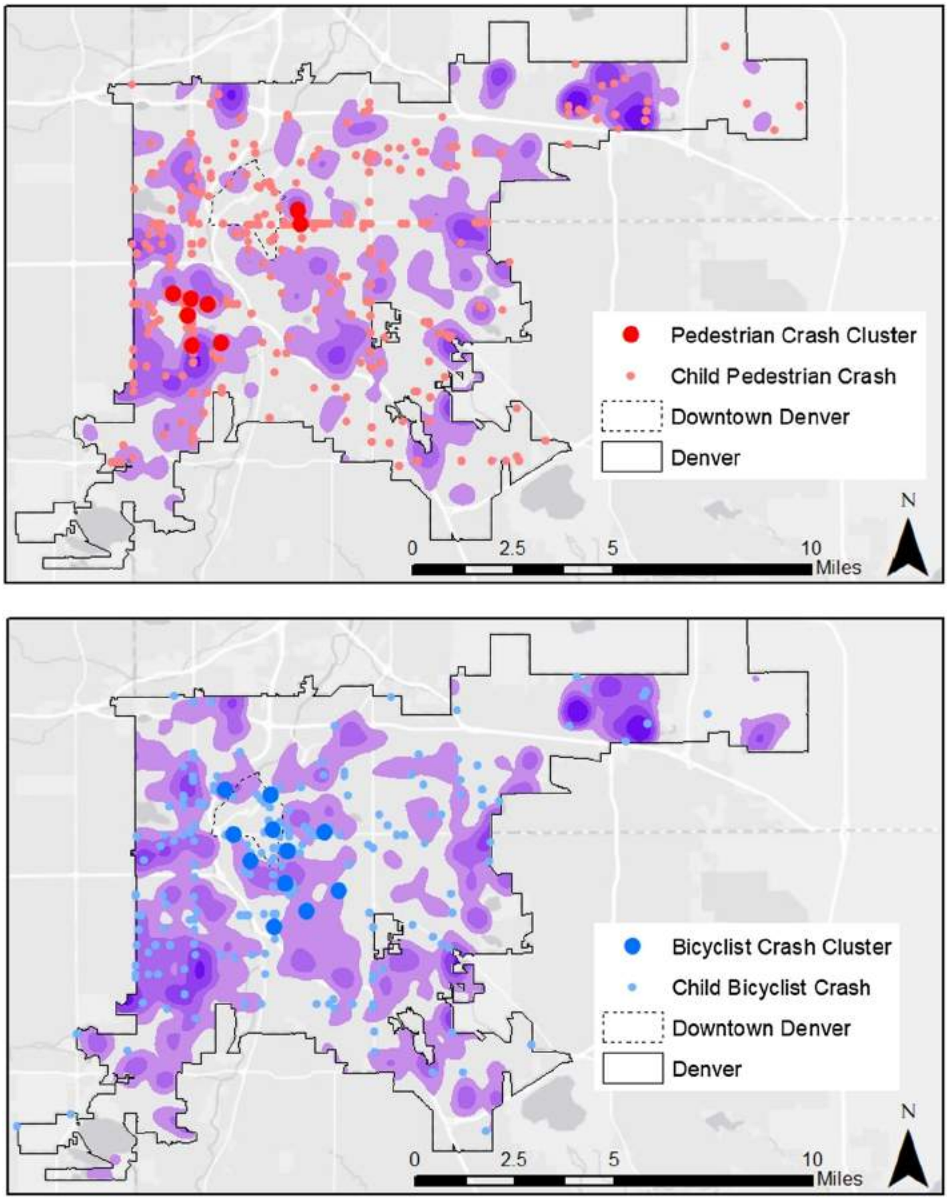


**Fig. 9.** Spatial comparison of crash-based reactive analyses and proactive analysis (pedestrian on top; bicycle on bottom; dark = higher concentration).

Taking a closer look at the results, we can see that – along with identifying hidden safety issues – the proactive analysis can present fine-grained traffic safety results. By identifying a single point as a crash hotspot through a reactive analysis, we cannot understand the larger context of the issue. Similarly, by identifying a lengthy high-crash corridor, we cannot know exactly where the issue is or what is causing it. With the proactive analysis, however, an analyst can observe where trips should be occurring and what might be blocking them. Fig. 11 shows that there are distinct clusters of suppressed trips throughout neighborhoods in Denver that do not necessarily fall on a major corridor or at a major intersection. One single gap in a sidewalk could possibly suppress children over a three-block area (Fig. 11). While a single missing sidewalk does not constitute a major safety issue from a crash-based perspective, it is a major safety issue for this particular neighborhood and can be effectively identified through a proactive analysis. Not only do the results of the proactive analysis present new and important findings, but the associated output presents a more practical way of considering and addressing pedestrian and bicyclist safety.

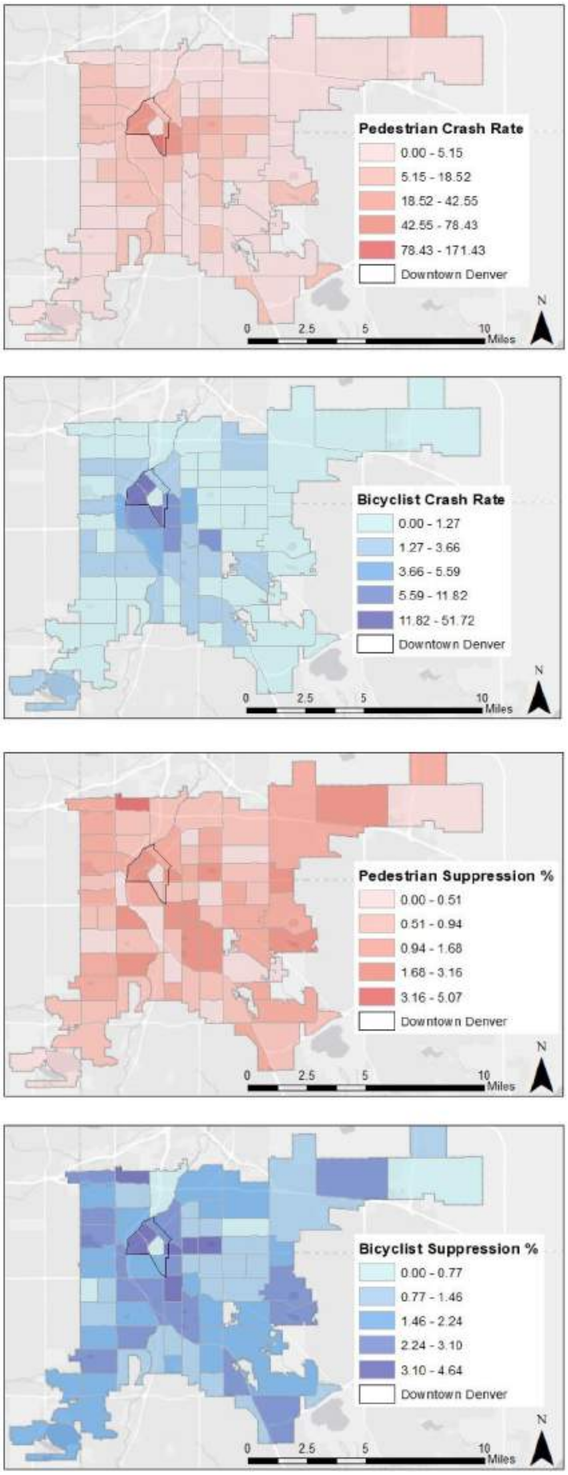


**Fig. 10.** Choropleth comparison of crash-based reactive analyses and proactive analysis (crash rate per thousand).


**Fig. 11.** Example of pedestrian trips experiencing suppression.

## 6. Discussion

While this work provides a methodology to develop a proactive safety analysis tool, the methodology does employ some assumptions that can be improved through future work. Excluding levels of non-motorized exposure was a limitation. Including non-motorized exposure would provide a clearer picture, especially by allowing for more representative crash rates in the reactive analysis. However, non-motorized exposure is difficult to obtain and was not used in the existing agency-produced reports either.

Future work would benefit from user counts or volumes to better understand where trips are occurring and the accuracy of the trip suppression estimations.

Furthermore, pedestrian and bicyclist trip purpose may have been inconsistent among the different analyses. All analyses, however, were for users of the same age. Because of the concentration of children in Denver and the location of roadway characteristics perceived as unsafe, we believe that suppressed child trips would be similarly clustered regardless of trip purpose. Future work will hopefully move toward a more holistic model for all ages and trip purposes. Additionally, we would gain a better understanding of trip suppression by accounting for the characteristics of crossings (e.g. signalization, phasing, turning movements, crosswalks, refuge islands, etc.) as well as other levels of the current variables that we did not test in the present iteration. Further exploring the impact of vehicle volumes beyond the current binary low/high definition would be beneficial to subsequent work. Finally, there were other factors – such as crime and socioeconomics – that influence trip suppression and would be worthy to examine in future analyses.

## 7. Conclusion

Conventional crash-based analyses help identify areas with active transportation safety problems. However, these reactive analyses can only find locations where walking and bicycling levels are high enough to allow safety issues to manifest themselves. The proactive analysis that we propose in this paper can identify active transportation safety concerns that a crash-based, reactive analysis may miss. By recognizing places where perceived safety concerns have lowered walking and bicycling trips – enough to effectively reduce crashes and hide safety issues from sight – we furnish ourselves with a new lens through which we can better understand latent active transportation safety issues.

Findings suggest that proactive safety analyses can effectively complement traditional reactive approaches. Cities that wish to obtain a holistic perspective of their streets' safety would be prudent to consider both manifested and latent pedestrian and bicyclist safety issues. While we recommend that other cities administer their own survey to account for city-specific traffic safety perceptions, this paper provides a framework to accomplish more comprehensive traffic safety analyses. The research fills a critical gap in the literature by showing the importance of proactive safety analyses and providing methods to accomplish such analyses.

Both reactive and proactive safety analyses provide unique and important perspectives on traffic safety. If our goal is to enable more people to safely walk and bike as opposed to simply reducing crashes, then it is imperative to consider active transportation traffic safety proactively.

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## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2019.03.010.

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