Caltrans Active Transportation Benefit – Cost Tool

Technical Documentation

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1. Introduction

This document provides the technical details for the calculations and assumptions of the Caltrans Active Transportation Benefit-Cost tool[1] hosted by UC Davis. The tool was designed by UC Davis in partnership with the Caltrans Active Transportation Resource Center (ATRC)[2] and guided by a technical advisory committee made up of members of local, regional, and state government agencies, community groups, and academics. The primary goal of the tool is to provide a unified framework for valuing the benefits of active transportation projects in California to support state-level programs like the California Active Transportation Program (ATP), and to help inform practitioners of the wide-ranging benefits of active transportation investments.

The tool development began with outreach and collaboration in 2020 through surveys and focus groups with members of the California ATP Technical Advisory Committee and other state agencies and communities. From 2020 through 2021, UC Davis held numerous workshops with the technical advisory committee for the project to design the scope and structure of the tool. Those workshops led to a tool framework designed to:

(1) Enable calculation of the estimated benefits from proposed active transportation projects (infrastructure and programs).
(2) Provide uniform calculation methods to be applied statewide that are accessible for all active transportation project implementors and funders.
(3) Provide estimates that are context sensitive.
(4) Communicate all the benefits that active transportation projects produce given the available evidence. Where evidence is uncertain or missing, qualitative evidence should be provided.
(5) Allow users to learn about how to design more benefit-producing and cost-effective projects by using the tool in the design phase of a project.

The tool is a project-level benefit calculator, not a traditional benefit-cost tool. Costs are provided by the user, and intervention benefit quantities are calculated when quantitative

[1] https://activetravelbenefits.ucdavis.edu/ and source code: https://github.com/bicyclingplus/caltrans-bc-tool
[2] https://caatpresources.org/

evidence is available. Where evidence on the impacts of interventions is suggestive of benefits but quantitative evidence is lacking, the tool reports qualitative outcomes. The current version of the tool calculates benefits in units specific to benefit categories (e.g., emissions, physical activity); it does not monetize benefits. Future versions of the tool could incorporate economic value assumptions and calculate traditional cost to benefit ratios.

This tool is a first attempt at quantifying the benefits of active transportation projects. It has several limitations, which are described throughout this documentation. Each of these limitations offer opportunities for continued improvement of the tool.

2. Tool Overview and Data Sources

Conceptually the tool blends the simplicity of calculators based on effect sizes (or elasticities) with the sophistication and richness of available geographic information systems (GIS). The tool has five steps:

1. Data Preparation
2. User Input
3. Active Travel Estimation
4. Estimated Change in Active Travel
5. Estimated Benefits

The tool relies on findings, usually in the form of effect sizes or elasticities, from previous studies as summarized in the accompanying literature review.[3] These effects sizes are used in estimating the change in active travel and in estimating benefits. The tool incorporates an original model for predicting active travel activity that was estimated using data listed in Table 1. The tool queries a custom-built GIS layer and look up tables that hold effect sizes from the accompanying literature review. Other data such as specific parameters for benefit calculations are described in the following sections. The custom GIS layer is built from several data sources, some of which are prevalent and publicly available (e.g., American Community Survey, Open Street Maps), some of which were built specifically for this tool (e.g., PeopleForBikes Bike Network Analysis accessibility scores), and some of which entailed partnership with private companies (e.g., Strava Metro estimates of bicycling volume).

[3] https://activetravelbenefits.ucdavis.edu/litreview

Table 1. Data Sources and Use

Data source	Data Type	Data Processing	Purpose	Tool use
Open Street Maps (OSM)	road characteristics	Filtering and reclassifying	Web mapping, activity estimation	Tiles from Mapbox
Strava Metro	filtered OSM GIS	None	Web mapping, activity estimation	None, intermediate data
Custom GIS network layers	Filtered and expanded OSM GIS	Strava Metro's version of OSM with added attributes	Web map selection, baseline activity, baseline safety	Yes, selectable GIS features
San Diego Association of Governments (SANDAG)	permanent bike counts	None	Activity estimation	None, intermediate data
San Francisco Municipal Transportation Agency (SFMTA)	permanent bike counts	None	Activity estimation	None, intermediate data
Caltrans (District 1)	temporary bike counts	None	Activity estimation	None, intermediate data
Griswold et. al. (2018)	estimated pedestrian crossing volumes	None	Activity estimation	None, intermediate data
PeopleForBikes	accessibility metrics	Inverse distance weighting	Activity estimation	None, intermediate data
NOAA	weather	None	Activity estimation	None, intermediate data
California Household Travel Survey (CHTS)	Trip distances	Weighted histogram	Activity estimation	Yes, lookup table
Literature Review Effect Sizes	Percent change	Extraction and synthesis	Benefit calculations	Yes, lookup tables

Data and estimated values in the first three steps of this tool (Data Preparation, User Input, and Active Travel Estimation) are assumed to be error free. Future revisions to the tool should consider incorporating uncertainty (especially in the Active Travel Estimation step) into this tool. Data and calculations in the last two steps (Estimated Change in Active Travel, and Estimated

Benefits) consider the uncertainty in the effect sizes (elasticities) found in the corresponding literature review by providing three estimates (low, average, high) in the output tables. The three values reflect the variability between studies and give an indication of the uncertainty in the calculations. The values are selected from studies that use a variety of designs and statistical analyses. They are not estimated through a formal meta-analysis. As research on active travel benefits continues to grow, future versions of this tool should consider revising estimates with formal meta-analyses.

All benefits and intermediate estimates are first calculated at either the daily or annual level. Daily values are assumed to be daily annual averages and multiplied by 365 to be comparable to annual estimates (e.g., daily bike miles traveled for a project is multiplied by 365). Once all values are at the annual level, depending on the user defined project time frame, benefits are calculated as a net present benefit (currently only 1 year and 20 years are allowed) and with a 4% discount rate.[4] Future versions of this tool should consider alternative project time frames or project time frames that vary by project element given the wide variety of lifetimes for different active transportation project elements. The net present benefit (NPB) equation the tool uses is:

$$NPB_b = \sum_{t=1}^{n} \left(\frac{A_b}{(1+r)^t} \right)$$

where:

t	=	1, …, n
n	=	Total number of years
b	=	Benefit
A_b	=	Annual benefit estimate
r	=	Discount rate (0.04)

The tool reports benefits in three ways: absolute values, relative to the surrounding residential population, and relative to the surrounding number of jobs. Depending on the goals of a specific project, one or more of these metrics may be appropriate for communicating the benefits.

[4] We use the default rate from the Caltrans Transportation Economics tools (https://dot.ca.gov/programs/transportation-planning/division-of-transportation-planning/data-analytics-services/transportation-economics/cal-bc-training)

3. User Inputs

3.1 Project Details

The user is required (or requested) to provide the following input parameters about the proposed active transportation project:

- County (required): This parameter is used to center the map and for emissions estimates.
- Project Name (optional): This parameter name or description is used to help identify the project. If left blank, the tool reports "Not Provided."
- Project Cost (in dollars) (optional): This parameter is reported in the output. If left blank, the tool reports "Not Provided."
- Project Time Frame (required, default is 20 years): This parameter defines the timeframe for calculating benefits.
- Project Type (select one of three categories, required): This parameter filters the dialog for entering project information.
  - Infrastructure
  - Non-Infrastructure
  - Infrastructure and Non-Infrastructure
- Active Travel Type (select one of three categories, required except for when Project Type = Non-Infrastructure): This parameter filters the benefit calculations by modes targeted.
  - Bicycle only
  - Pedestrian only
  - Bicycle and Pedestrian
- Transit Connections (required): This parameter is used in the calculation of mode substitution for new walk trips.
  - Connections to major transit hub(s)
  - Connections to transit stop(s)
  - No transit connections
- Safety Data (optional): These parameters are used for safety benefit calculations. User could include local data from police departments or hospital records, but also subsets of SWITRS data that are specific to the project.

Safety Outcome	Bicyclist		Pedestrian	
	Intersections	Roadways	Intersections	Roadways
Crashes				
Injuries				
Deaths				

While this is a project-level tool, the tool has the option of loading past saved projects (projects that were exported, see accompanying User Guide). Loading past projects allows for easier program level calculations by querying the benefit calculations of program funded projects.

3.2 Project Reach

Using the map interface, the user selects the roadway segments (links) and intersections (nodes) that represent the project reach. The base maps are Mapbox hosted OSM tiles, and the tool includes a network overlay that is a filtered and processed version of the OSM California road network (as processed by Strava Metro). This overlap is displayed for user selection of links and nodes. The Strava Metro network is the OSM network used by Strava, a fitness and activity application with a global user base of ninety-five million in 2021 (Strava, 2021). The primary difference between the raw OSM network and the one Strava has processed is that the Strava network includes a unique link between every node. These links are practical for use in this tool as they are smaller in length than the OSM links and can be selected based on the project scope by the user. The junctions and endpoints of all links were used to generate nodes that represent all potential intersections to be selected for inclusion in a project. By default, when selecting a link, the connecting nodes are included in the project, but they can be deselected by the user. If a proposed project includes adding new road links or intersections to the network, the user has an option to create these manually on the map.

Once the user selects or creates the road links and nodes that correspond to the project, the tool estimates the "project reach." The project reach is the sum of the length of all selected and digitized links, and the sum of all selected and digitized nodes. A network attribute indicates if a given road link is one-way or two-way. If a selected link is a one-way link, its length is added directly to the total project length. If the link is a two-way link (most links on the map), it is assumed the project affects both directions of travel and its length is doubled and then added to the total project length. This assumption may result in an upward bias of project reach for projects primarily focusing on one direction of travel. This upward bias in project reach may result in a downward bias some benefits. Future versions of this tool could include a more precise measure of project reach.

3.3 Project Elements

Project elements refer to the active transportation infrastructure and program types that the user selects as part of the project. The project elements are divided into two categories: infrastructure and non-infrastructure. Those categories were based on the accompanying literature review[5] to

[5] https://activetravelbenefits.ucdavis.edu/litreview

understand the effects of infrastructure and non-infrastructure elements on active travel and the existing elements described in the California Active Transportation Program (ATP) application.[6] The tool uses a broad definition of "infrastructure" that includes not only traditional changes to the roadway but also interventions with traffic control (e.g., speed display signs) and amenities (e.g., bike parking). The types of infrastructure elements are further differentiated based on whether they are implemented on roadways (block faces) or at intersections (midblock crossings are considering intersections because traffic intersects) or if the intervention is an amenity or a multi-element intervention. Two types of project measurements are considered: length or count. If the project element is measured with length, feet is the measurement unit and if the project element is measured as a count, the count is considered an integer unit. For example, sidewalks are measured in feet while speed display signs are measured in counts (per unit). Table 2 shows the infrastructure and non-infrastructure elements, their classification, and their units with relevance to this tool. Each infrastructure intervention has one of three status levels: 1) New, 2) Significant Upgrade and 3) Retrofit or Maintenance. These levels are provided primarily to accommodate more refined estimations in future improvements to this tool. In the current version of the tool, all "New" and "Significant Upgrade" interventions are treated the same, and "Retrofit or Maintenance" elements are only given 10% of the benefits found in the literature.

Table 2: Infrastructure and non-infrastructure project elements

Intervention Class	Interventions	Measurement
Block Face	Bike shared lane markings (Sharrows, Class III)	Length
	Bike boulevard	Length
	Bike highway	Length
	Buffered bike lane (Class II)	Length
	Conventional bike lane (Class II)	Length
	Edge lanes (advisory lanes)	Length
	Horizontal deflector	Count
	Lane narrowing	Length
	Multi-use path	Length
	Off-street bike path (side paths included, Class I)	Length
	Road diet	Length
	Protected bike lane (Class IV)	Length
	Open street	Length
	Sidewalk	Length
	Dynamic speed display sign	Count

[6] https://catc.ca.gov/programs/active-transportation-program

	Speed limit reduction	Count
	Vertical deflector	Count
	Lighting	Count
Intersection	Ada ramps	Length
	Signal phasing	Count
	Lighting	Count
	Ada pedestrian signal	Count
	Bike box (turn or cue)	Count
	Bike signal	Count
	Crossing island	Count
	Crosswalk	Length
	Curb extension	Length
	Pedestrian countdown	Count
	Pedestrian scramble	Count
	Protected intersection	Count
	Raised crossing	Count
	Raised intersection	Count
	Roundabout	Count
	Traffic signal	Count
	Flashing beacon	Count
	Shorten crossing	Count
	Repaving	Length
Amenity	Bike parking	Count
	Bikeshare infrastructure	Count
	Landscaping	Count
	Wayfinding signs	Count
Non-Infrastructure Elements	Safe routes to school	
	Community events	
	Social marketing, education, or campaigns	
	Active transportation experiments	
	Programs to decrease car use	
	Programs to connect to transit	

After the user selects the project elements from a drop-down menu, a dialog to input the length or count of each project element is provided. Users provide the amount of each element at the project level, not at individual link or node levels.

4. Estimate Existing Active Travel

If the proposed project includes infrastructure elements, the tool estimates the existing bicycle and pedestrian active travel that crosses any part of the project reach based on the bicycle and pedestrian statistical models developed by Kamalapuram (2022). The statistical models are of

Annual Average Daily Bicycle Traffic (AADBT) and Annual Average Daily Pedestrian Traffic AADPT calculated from bicycle and pedestrian counts, built using the Random Forest machine learning algorithm. This is known as a "direct demand" approach to estimate active travel volumes. Based on the availability of bike and pedestrian count data (Table 2), the model estimates bicycle travel on the links and pedestrian travel at the intersections. Data for the explanatory variables come from the Strava Fitness app (acquired through Strava Metro), network accessibility metrics from the Bicycle Network Analysis (BNA) tool from PeopleforBikes, roadway characteristics from Open Street Map (OSM), census tract characteristics, and weather data. The following sections provide a summary of the data sources and steps followed to estimate AADBT and AADPT across the road network of California.

4.1 Dependent variables

4.1.1 AADBT from bicycle counts

Permanent and short-term bike counts were used to develop the models of AADBT. A permanent count location is defined as one where data is collected for more than seven days each year (>7 days/year), whereas a short-term count location is one where data is collected for less than seven days each year (<= 7 days/year).

Permanent count data come from locations in the cities of San Francisco (2018-2019) and San Diego (2016-2019) that were collected by the San Francisco Municipal Transportation Authority (SFMTA) and San Diego Association of Governments (SANDAG) respectively. Short-term counts were obtained from Caltrans District 1 consisting of counts at numerous locations in Del Norte, Humboldt, Lake, and Mendocino counties. From June 2014 to September 2019, data was collected for 1-7 days at each location. The duration of counts varies by location, from 10-15 hours per day. To eliminate volume disparities in 2020 owing to the COVID -19 pandemic, all count data from January 2016 to December 2019 were filtered and retained. Figure 1 shows the bicycle counter locations.

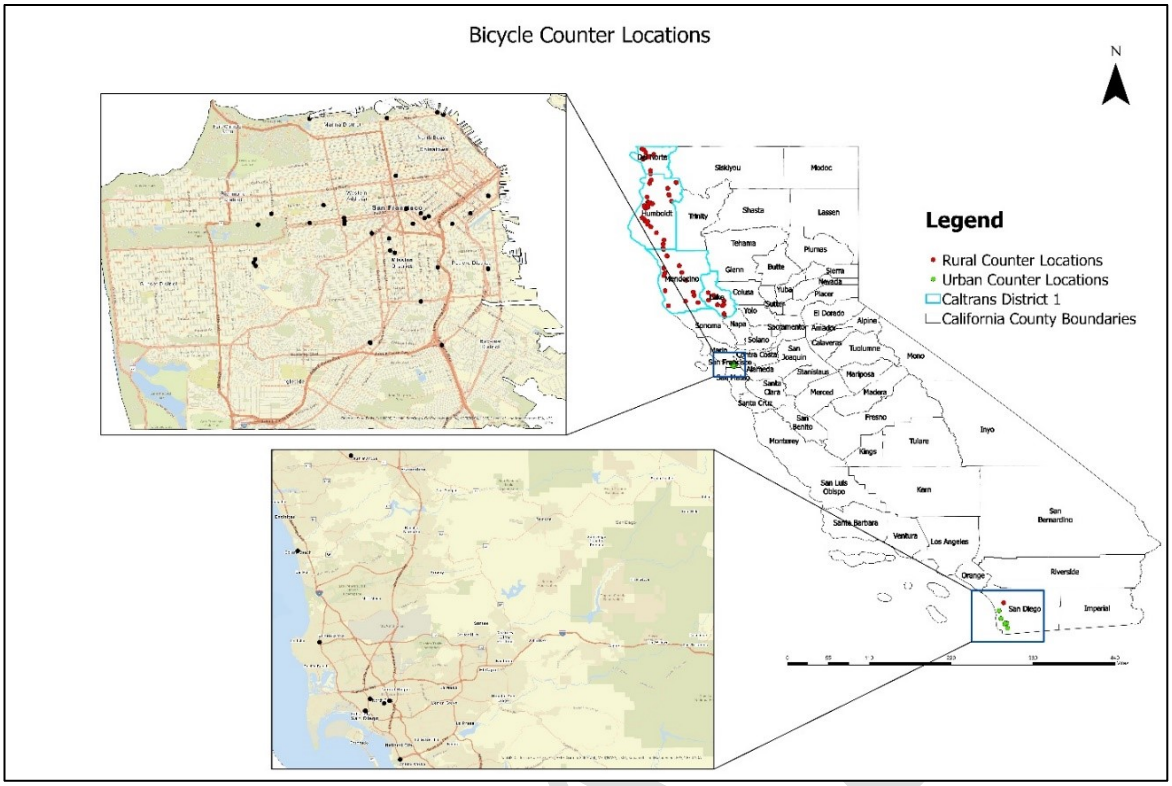

Figure 1: Bicycle Counter Locations

The number of missing days in full year counts from San Francisco and San Diego is near zero and thus a simple average of daily bicycle volume is used to calculate AADBT. The one exception is in San Francisco, where no count data was available from August 2019 to December 2019. Although data for only half the year was available, the available daily bike volume was averaged based on the assumption that it represented AADBT. This simplification may have resulted in biased estimates in 2019, and future revisions to the tool should consider an alternate approach. For Caltrans District 1, short-term counts were assumed to be indicative of the daily counts although it is well known that counts of this brief duration result in biased estimates of annual averages (Laustsen et al., 2016), because no other rural bike count data was available, these averages were assumed to represent annual averages. As more count data become available, future revisions to the models should be considered.

Since the nature of counts (permanent vs. short-term) vary from San Francisco and San Diego to Caltrans District 1, and the locations in rural areas are limited to only four counties in California, the data were segmented by the neighborhood type of the census tract corresponding to the counter's location based on the classification from Salon and Handy (2014) for estimating two models as follows:

1. Urban model: central city, urban and suburban neighborhood types
2. Rural model: rural neighborhood type

4.1.2 AADPT from pedestrian counts

The dependent variable for the pedestrian activity models is the annual intersection pedestrian crossing volume estimates normalized to 2016 population from Griswold et al., (2018) divided by 365 to get the AADPT. A limitation with this dependent variable is that it is an estimate of annual intersection crossing volumes (short-term counts factored into annual estimates) and is thus subject to unknown errors.

Figure 2 shows the locations of the pedestrian counts. In contrast to the bicycle counter locations, pedestrian count locations have greater geographic diversity. Because of the uniformity in the response variable and the greater geographic diversity, one generalized pedestrian activity model was estimated using all the study locations.

4.2 Explanatory Variables

The explanatory (predictor) variables used for estimating active travel are shown in Table 3 with their data sources and data types. Each data category and source are discussed in subsequent sub-sections.

4.2.1 Strava Metro

For the road links closest to the latitude and longitude of the counter locations, Strava trip counts were obtained from the Strava Metro website. Strava Metro data is available for streets only, not the intersections. Therefore, Strava counts were used only in the bicycle activity model and not in the pedestrian activity model. Future model revisions should consider Strava running and walking counts on intersection adjoining roads.

Figure 2: Pedestrian Counter Locations

Table 3 Variables Considered for Active Travel Model Development

Category	Data Source	Variable	Data Type
Strava counts	Strava Metro	Total number of trips	Numeric
		Number of commute trips	
		Number of leisure trips	
		Number of morning trips	
		Number of evening trips	
		Total number of riders	
		Number of male riders	
		Number of female riders	
		Number of riders aged 13 - 19 years	
		Number of riders aged 20 - 34 years	

Category	Data Source	Variable	Data Type
		Number of riders aged 35 - 54 years	
		Number of riders aged 55 - 64 years	
		Number of riders aged 65 and above	
Network Accessibility Metrics	Bike Network Analysis (BNA)	Population in other census blocks that can be accessed via low stress connections from this block	Numeric
		Population in other census blocks that can be accessed via all connections from this block	
		Jobs in other census blocks that can be accessed via low stress connections from this block	
		Jobs in other census blocks that can be accessed via all connections from this block	
		K-12 schools in other census blocks that can be accessed via low stress connections from this block	
		K-12 schools in other census blocks that can be accessed via all connections from this block	
		Universities in other census blocks that can be accessed via low stress connections from this block	
		Universities in other census blocks that can be accessed via all connections from this block	Numeric
		Tech/vocational colleges in other census blocks that can be accessed via low stress connections from this block	
		Tech/vocational colleges in other census blocks that can be accessed via all connections from this block	
		Doctor offices in other census blocks that can be accessed via low stress connections from this block	
		Doctor offices in other census blocks that can be accessed via all connections from this block	
		Dentist offices in other census blocks that can be accessed via low stress connections from this block	
		Dentist offices in other census blocks that can be accessed via all connections from this block	
		Hospitals in other census blocks that can be accessed via low stress connections from this block	
		Hospitals in other census blocks that can be accessed via all connections from this block	
		Pharmacies in other census blocks that can be accessed via low stress connections from this block	
		Pharmacies in other census blocks that can be accessed via all connections from this block	
		Retail centers in other census blocks that can be accessed via low stress connections from this block	

Category	Data Source	Variable	Data Type
		Retail centers in other census blocks that can be accessed via all connections from this block	
		Supermarkets and groceries in other census blocks that can be accessed via low stress connections from this block	
		Supermarkets and groceries in other census blocks that can be accessed via all connections from this block	
		Social services in other census blocks that can be accessed via low stress connections from this block	Numeric
		Social services in other census blocks that can be accessed via all connections from this block	
		Parks in other census blocks that can be accessed via low stress connections from this block	
		Parks in other census blocks that can be accessed via all connections from this block	
		Trails in other census blocks that can be accessed via low stress connections from this block	
		Trails in other census blocks that can be accessed via all connections from this block	
		Community centers in other census blocks that can be accessed via low stress connections from this block	
		Community centers in other census blocks that can be accessed via all connections from this block	
		Transit hubs in other census blocks that can be accessed via low stress connections from this block	
		Transit hubs in other census blocks that can be accessed via all connections from this block	
Roadway characteristics	Bike Network Analysis (BNA)	Open Street Map Functional Class	Categorical Levels: path, residential, tertiary, tertiary_link, secondary, secondary_link, primary, primary_link, trunk, trunk_link, motorway, motorway_link
		Speed limit	Numeric
		One way for car traffic	Categorical: Levels: Yes, No
		One way for bike traffic	Categorical: Levels: Yes, No

Category	Data Source	Variable	Data Type
		Presence of bike infrastructure	Categorical: Levels: Yes, No
Census Tract Level Variables	Salon & Handy (2014)	Neighborhood type	Categorical Levels: Suburb, Urban, Rural, Central City
	2015 ACS 5 - Year Estimates	Percent of commuters using transit	Numeric
		Percent of commuters using walk	
		Percent of commuters using bike	
		Percent of male population	
		Percent of female population	
		Median household income	
		Percent of While alone population	
		Percent of Black or African American alone population	
		Percent of Asian alone population	
		Percent of American Indians alone population	
		Percent of Hispanic or Latino population	
	SWITRS dataset	Number of severe injuries	Numeric
		Number of visible injuries	
		Number of complaints of pain	
		Number of pedestrians killed	
		Number of pedestrians injured	
		Number of bicyclists killed	
		Number of bicyclists injured	
Weather data	National Oceanic and Atmospheric Administration (NOAA)	Daily precipitation (mm)	Numeric
		Minimum daily temperature (degrees F)	
		Maximum daily temperature (degrees F)	

4.2.2 Network Accessibility Metrics

The network accessibility metrics used in this study are the low and high-stress connections of census blocks from PeopleForBikes' Bicycle Network Analysis (BNA) tool. The low- and high-stress classification is loosely based on the classifications designed to differentiate road environments that are comfortable and accommodating (low-stress) and those that are uncomfortable and unaccommodating (high-stress) in terms of bicycling (Furth and Mekuria, 2013; Mekuria et al., 2012). The BNA tool uses a computationally intensive routing algorithm that calculates census block-level accessibility metrics for several activity types.[7] Travel distances of 1.67 miles for biking (the BNA tool default distance), and 0.25 miles for walking were used. The accessibility percentages for count location were aggregated by weighing the scores of surrounding census blocks by the square of the inverse of its distance to the count location (known as Inverse Distance Weighting (IDW)). This weighted aggregation puts greater emphasis for accessibility at the count location than at travel distances farther from the count location.

4.2.3 Roadway characteristics

Roadway characteristics are included as predictors in the bicycle count model (not the pedestrian count model) and were obtained from intermediate data from the BNA tool which queries OSM for roadway functional classification, speed limit, presence of bike lanes using OSM tags.

4.2.4 Census tract characteristics

Variables defined at the census tract level came from two data sources. The first is the US Census Bureau American Community Survey (5-year estimates). Characteristics such as race, gender, income, commute to work were included (see Table 3). The second is the California Highway Patrol Statewide Integrated Traffic Records System (SWITRS) dataset which holds bicycle and pedestrian crash data. To correspond with the date ranges of bicycle and pedestrian counts, bicycle crash data from 2016-2019 and pedestrian crash data for 2016 were spatially joined with the California census tracts, and the number of crashes in each census tract were aggregated to the corresponding year.

4.2.5 Weather data

Both the bicycle and pedestrian models include annual average precipitation, and both minimum and maximum temperature, all obtained from the National Oceanic and Atmospheric Administration (NOAA). To match this data to count locations, the closest weather station to every counter location was first retrieved. If the data at the closest station was not available for the required year, data from the next nearby station was used. All count locations had a weather station within thirty-one miles (50km).

[7] Further details about the BNA methodology can be found here: https://bna.peopleforbikes.org/#/methodology. We used the intermediate outputs from the destination analysis prior to the BNA scoring criteria. The data represent percent of people in a census block with access to each destination type by low and high stress on the OSM network within the defined distance thresholds.

4.3 Bicycle models

Table 4 shows the performance metrics for the two bicycle count models by root mean square error (RMSE), mean absolute error (MAE), and mead absolute percent error (MAPE). The errors are averages from k-fold cross validation and represent the expected out-of-sample prediction error (Kamalapuram, 2022). Error margins (Table 5) and plots of predictive accuracy (Figure 3) are also reported to illustrate the accuracy and precision of the models. Improving the accuracy and precision of the models by collecting more data and exploring alternative model formulations should be considered in future revisions to the tool.

Table 4: Random Forest Model Performance (Bicycle Models)

	Urban (B_UM2)	**Rural (B_RM2)**
RMSE	265	4.96
MAE	160	3.75
MAPE	0.39	1.05

Table 5: Error Margins of Predicted AADBT (Bicycle Models)

Study Area	**Number of data points***	**% Of data points predicted**	**Error margins of predicted AADBT**
Urban	132	25%	±21
		50%	±57
		75%	±190
		99%	±1000
Rural	184	25%	±1
		50%	±3
		75%	±5
		99%	±16

*Number of data points denotes AADBT per location per year.

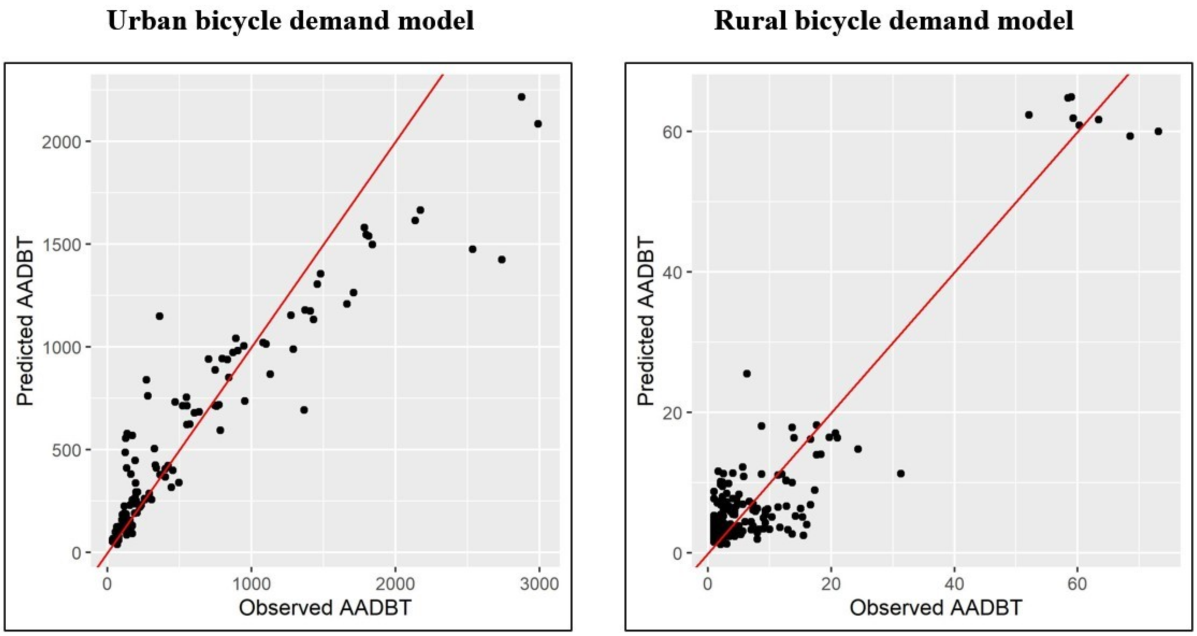

Figure 3: Observed vs Predicted AADBT for bicycle demand models with the network accessibility metrics

4.4 Pedestrian model

Table 6 shows the performance metrics for the generalized (across urban and rural environments) pedestrian models through the same cross validation procedure as described in Section 4.3. Table 7 and Figure 4 show the error margins and visual scatter plot of predicted AADPT when compared to the observed values.

Table 6: Random Forest model performance - Pedestrian models

RMSE	1647.58
MAE	884.11
MAPE	7.69

Table 7: Error Margins of Predicted AADPT

Number of locations	% Of locations predicted	Error margins of predicted AADPT
1238	25%	±137
	50%	±367
	75%	±1000
	99%	±7380

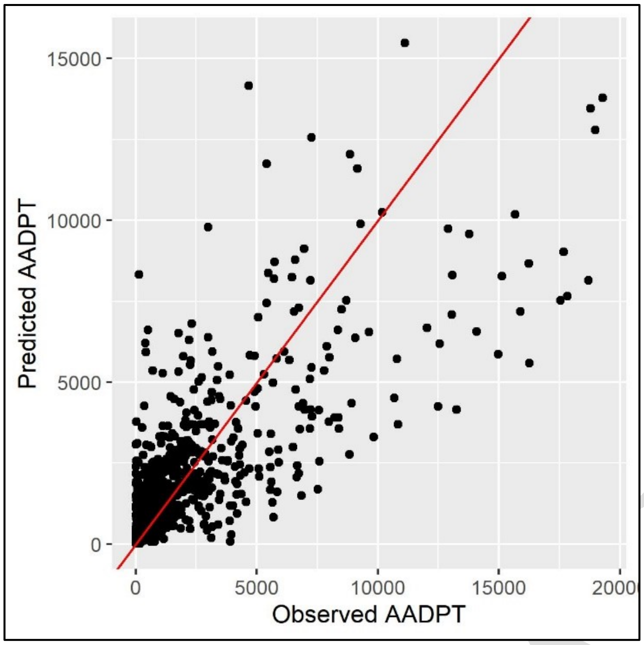

Figure 4: Observed vs Predicted AADPT for pedestrian model

4.5 Application of models for estimating active travel networkwide

The estimated models are applied across the entire network GIS layer in the tool to predict the AADBT for every link and the AADPT (crossing volumes) at every node. When a user selects a link or node on the map, the tool queries the corresponding predicted AADBT or AADPT in the background.[8] Because the models of active travel include a wide variety of variables relating to accessibility, the estimates provide context-sensitive predictions of current active travel.

4.5.1 Bike and Walk Miles Traveled

The count models predict bike traffic volumes at the roadway (link) level and pedestrian crossing volumes at the intersection (node) level. These estimates of volumes are converted to expected project-level active travel (in distance) through the following steps:

(1) Calculate the average project length per unit volume (i.e., walking, bicycling).
(2) Using trip distance summaries from the 2012 CHTS (Table 8), and the average length per unit (from step 1), find the distribution of percentage of trips traveling through the units.

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[8] If the user creates a new road link or node on the network, the average AADBT of other selected road links in the project is calculated and assumed to be the AADBT of the new link. If the entire project reach is composed of new links and nodes, the tool gives a warning about not displaying quantitative benefits and only reports qualitative benefits.

(3) Calculate the total number of units people travel through according to the distribution of trips by distance (step 2). For all distance bins in Table 8, multiply the number of units by the percentage of trips (fraction) and sum.

(4) Calculate the number of unique trips by dividing the total project volume by the total number of units travelled (from step 3).

(5) Multiply the number of unique trips by the fraction of trips in each distance bin and by the distance for each mode in Table 8 to estimate the total bike miles traveled (BMT) and total pedestrian miles traveled (PMT) of trips that pass through the project reach.

This algorithm assumes that the travelers in the project travel like the general population in the 2012 CHTS in terms of trip distances. It also does not include any data on travel behavior at the project location which likely results in added uncertainty.

Table 8. Person-weighted fraction of trips by distance bin in the 2012 CHTS

Walk		Bike	
distance (miles)	**percentage of trips**	**distance (miles)**	**percentage of trips**
0.1	0.10	0.25	0.198
0.2	0.17	0.75	0.271
0.3	0.16	1.25	0.174
0.4	0.12	1.75	0.094
0.5	0.09	2.25	0.063
0.6	0.07	2.75	0.034
0.7	0.06	3.25	0.039
0.8	0.04	3.75	0.028
0.9	0.03	4.25	0.014
1.0	0.03	4.75	0.010
1.2	0.02	5.25	0.013
1.1	0.02	5.75	0.010
1.3	0.01	6.25	0.007
1.4	0.01	12.5*	0.045
1.5	0.01		
1.6	0.01		
1.7	0.01		
1.8*	0.04		

* Trips above 1.7 miles for walking and 6.25 miles for bicycling were aggregated into one bin and assigned the weighted average for distance.

5. Estimated Change in Active Travel

5.1 Estimating Increase in Active Travel

Table 9 and Table 10 show the bicycle and pedestrian project elements that were found in the literature review to produce measurable increases in active travel. Given the variability of results from the literature, low, average, and high estimates for each project element are provided. If the literature review included meta-analyses with mean effects across studies, the average was set at the meta-analysis value. If no meta-analysis existed for specific study results, the range from the studies available was recorded and the average value set at the midpoint in the range. If only one quantitative study was available for a project element's effects and it only provided a mean value, we assumed wide range of 50% of the mean subtracted and added to estimate the low and high (up to 99%) values, respectively. Many of these values required interpretation of the study design, statistical analysis, and reported results documented in the literature review[9] to generalize to a percent change.

Table 9: Projects Elements Accounting for Increase in Active Travel (Bicycle)

Project Element	Class	Increase in Active Travel (percent)		
		Low	Average	High
Bike Highway	Roadway	38.5%	77%	115.5%
Buffered Bike Lane	Roadway	77%	174%	271%
Conventional Bike Lane	Roadway	-21%	124%	268%
Protected Bike Lane	Roadway	21%	96%	171%
Road Diet	Roadway	6.5%	13%	25%

Table 10: Projects Elements Accounting for Increase in Active Travel (Pedestrian)

Project Element	Class	Increase in Active Travel (percent)		
		Low	Average	High
Crossing Island	Intersection	5%	10%	15%
Road diet	Roadway	7.5%	15%	30%
Sidewalk	Roadway	12%	23%	33%

[9] https://activetravelbenefits.ucdavis.edu/litreview

If the user selects any of the above elements as part of the project interventions, the tool estimates the total Increase in Active Travel (miles) by mode (bicycling miles traveled (BMT) and pedestrian miles traveled (PMT) using the following equation.

$$Increase\ in\ Active\ Travel_{\ m} = \sum_{i=1}^{n} (AT_m * (E_i) * \frac{N_i}{L} * I)$$

where:

i	=	1, …, n
n	=	Total number of project elements selected by the user that influence increases in active travel
m	=	Mode of travel
AT	=	Existing active travel in miles, estimated from previous steps
E_i	=	Percentage (fractional) increase in active travel due to the project element (i)
N_i	=	Length or count of the project element (i)
L	=	Total project length or count
I	=	Improvement type $I = 1$ for New and Significant Upgrade $I = 0.1$ for Retrofit or Maintenance

For clarity, the calculation for each effect size estimate (i.e., low, average, high estimates) is not subscripted. This and all calculations for this tool that include low, average, and high estimates are completed and reported for each level independently.

5.2 Active Travel Demand Split

The estimated increase in active travel from Section 4.1 is split into four categories (Table 11) to calculate project-specific quantitative benefits. The first category (car shift) is the percent of the new travel that would have been made by car had the project not been built. This category is used for calculating the reduction in vehicle miles traveled (VMT) and the corresponding mobile emissions. For bicycling, the car shift fraction of distance is assumed to be one, meaning that each bike trip substitutes for a car trip of equal length. This assumption ignores the very probable possibility that the car trip the bike trip replaced might have been a longer trip (e.g., to a farther destination, because of routing or circling for parking, etc.). Future versions of this tool should consider adding complexity to account for this variability if data can be found to support it. Currently, this assumption makes calculations of substituted car travel distance conservative.

For walking, the car shift fraction is assumed to come from two cases: (1) a car trip replaced by a walk trip, and (2) a car trip replaced by a walk to transit trip. The same assumption of no change in trip distance as applied for the bicycling car shift is applied for the first case of car shift from walking. However, for the second case (the walk to transit trip replacing a car trip), the tool accounts for the distance of the car trip as being replaced by both walking and transit (a much greater distance) (see Section 5.3 for details of how this difference is applied to VMT reduction).

The fraction of new active travel that has shifted from other routes (Table 11 "Route Shift") is assumed to have the same distances as routes before the project. This assumption should be reconsidered in future versions of the tool as it is known that bicyclists value new infrastructure and likely ride out of their way (increasing travel distance) (Broach et al., 2012; Fitch and Handy, 2020).

Not all fractions of new travel are used in all benefit calculations. The last column of Table 11 shows which values are used for each calculation. For example, the fraction of new active travel that is induced (i.e., would not have happened had the project not been built) and shifted from all other modes of travel (e.g., transit) is included in the benefit calculations for safety and physical activity, but not VMT and emission reductions. This is because that travel is unlikely to reduce VMT given it did not replace any car travel at the trip level.

These assumptions are conservative because they are based at the trip level. Projects may change travel behavior in more impactful ways (e.g., someone choosing to bike for their entire day of travel because of a project). Future revisions to this tool could consider the potential for this added benefit if data can be found to support it.

Table 11: Mode Split for New Active Travel

Category	Fraction of New Trips*		Benefits calculated from fractions of new trips
	Bike	Pedestrian	
Car Shift	0.176	0.333	VMT/Emissions, Safety
Route Shift	0.588	0.773	Safety
Induced Travel	0.118	0.110	Safety, Physical Activity
Shift from Other Modes	0.118	0.480	Safety, Physical Activity

*Calculated as sample size weighted averages from data reported by Volker et. al., (2019b, 2019a)

6. Estimated Project-Specific Benefits

6.1 VMT Reductions

Mode substitution from car to walking or bicycling (car shift) reduces VMT. In this tool only the car shift fraction of new active travel is used to estimate the VMT reduced from the project. The following equation is used in calculating the VMT reduction.

$$Daily\ VMT\ Reduction = (B * CP * Cb) + \left(P * CP * Cw * (1 - Fwt)\right) + (P * Cw * Fwt * Tr)$$

where:

B	=	Daily bike miles traveled (BMT) increase
CP	=	Carpool factor (0.87)[10]
Cb	=	Car shift fraction for bicycling (0.176) (Table 11)
P	=	Daily pedestrian miles traveled (PMT) increase
Cw	=	Car shift fraction for walking (0.333) (Table 11)
Fwt	=	Fraction of new walk miles that connect to transit (0 for projects without a major transit connection emphasis, 0.1 for projects with connections to transit stations, and 0.5 for projects with a major transit hub connection)[11]
Tr	=	Transit connection factor for walk miles (13.67)

The *Tr* constant is assumed based on the following equation:

$$\mathrm{Tr} = \frac{Td * Fc}{Wd}$$

where:

Td	=	Transit trip distance (4.1 miles)[12]
Fc	=	Fraction of transit miles that are car mile reducing (0.5)[13]
Wd	=	Walk distance to transit (0.15 miles) [14]

[10] Parameter from Volker et. al., (2019b, 2019a) representing the reduction in car substitution miles from carpooling.

[11] Transit connection emphasis provided as input by the user. This parameter is not currently supported by empirical evidence but based on researcher expertise. Future revisions could include transit access metrics instead of user input. The downside to transit access metrics is the lack of ability to account for planned transit expansion in tandem with active transportation investment.

[12] Median transit trip distance (excluding long-distance train and bus) from the 2012 CHTS.

[13] Parameter based on authors' expertise, not empirical data. Future versions of this tool should consider revising them if data is available to support other values.

[14] Parameter based on authors' expertise, not empirical data. Future versions of this tool should consider revising them if data is available to support other values.

6.2 Emissions Reductions

VMT reductions (from Section 6.1) are used to estimate emissions reductions using values from the California Air Resources Board's (CARB) EMission FACtor (EMFAC) and fleet composition database (EMFAC2021 v1.0.1). Table X shows the specifications considered for obtaining the emission rates.

Table 11. CARB EMFAC Specifications

Specification	Description
Source	EMFAC2021 (v1.0.1) Emission Rates
Region type	County
Calendar year	2014 to 2050
Season	Annual
Vehicle Classification	Passenger Cars (LDA)
Units	grams/mile
Fuel type	Four categories: 1. Gasoline 2. Diesel 3. Electricity 4. Plug-in Hybrid
Pollutants	Greenhouse gases: 1. Carbon dioxide (CO_2) 2. Methane (CH_4) 3. Nitrous oxide (N_2O) Air Toxins: 1. Nitrogen oxides (NO_x) 2. Particulate Matter 2.5 (PM 2.5) 3. Particulate Matter 5 (PM 5) 4. Ammonia (NH_3) 5. Carbon monoxide (CO) 6. Sulphur oxides (SO_x)

The CARB fleet composition database gives the vehicle population aggregated at the county level by the vehicle category and fuel type (Table 12). The county for which a user of the tool originally selects to center the map is used to query these values.

Table 12. CARB Fleet Composition Specifications

Specification	Description
Source	CARB Fleet Web Database
Region type	County
Calendar year	2020
Vehicle category	Passenger Cars
Fuel type	Three categories: 1. Gasoline 2. Diesel 3. Electricity
Fuel Technology	Three categories:

	1. Internal Combustion Engine (ICE) 2. Battery Electric Vehicle (BEV) 3. Plug-in Hybrid Vehicle (PHEV)

Internal Combustion Engine (ICE) vehicles are divided into two categories based on the fuel type: gasoline or diesel. The fleet database consists of fuel type, fuel technology and vehicle population columns for each county in California (example shown in Table 13). Battery electric vehicles (BEVs) are assumed in EMFAC to have zero emissions. We calculate the vehicle proportion by dividing the vehicle population in each row by the total vehicle population in the county.

Table 13: Fleet Database Categorization for an Example County

County Name	Fuel Type	Fuel Technology	Vehicle Population	Vehicle Proportion
Los Angeles	Diesel	ICE	11275	0.003
Los Angeles	Electric	BEV	80082	0.022
Los Angeles	Gasoline	ICE	3496006	0.96
Los Angeles	Gasoline	PHEV	54620	0.015

The emission reductions are calculated using the following equation:

$$Emissions\ reductions_p = \left(\sum_{i=1}^{4} ER_{ip} * VP_i\right) * VMTR$$

where:

i	=	Fuel types: 1=Gasoline, 2=Diesel, 3=BEV, 4=PHEV
p	=	Pollutants
ER_{ip}	=	Emission rate
VP_i	=	Vehicle proportion
$VMTR$	=	VMT reduction calculated from Section 6.1

In the benefit outputs, pollutants are classified into two categories: Greenhouse gases and Air toxins. Greenhouse gases (GHGs) include carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) and air toxins include nitrogen oxides (NO_x), particulate matter (PM 2.5 and PM 5), ammonia (NH_3), carbon monoxide (CO) and sulphur oxides (SO_x). For GHGs, CO_2 equivalent emissions reductions are calculated based on the Global Warming Potential (GWP) values for a 100-year time horizon according to the International Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) (Myhre et al., 2013). Table 14 shows the GWP values for the GHGs considered by the tool for CO_2 equivalent calculations.

Table 14. Greenhouse Gas Global Warming Potentials

Greenhouse Gas	Global Warming Potential (GWP)
Carbon Dioxide (CO_2)	1
Methane (CH_4)	28
Nitrous oxide (N_2O)	265

Total CO_2 equivalent emissions reductions from GHGs is calculated using the following equation:

$$Total\ CO_2\ equivalent\ emissions\ reductions = \sum_{p=1}^{3} GWP_p * ERD_p$$

where:

p	=	GHG: 1=Carbon Dioxide (CO_2), 2=Methane (CH_4), 3=Nitrous oxide (N_2O)
GWP_p	=	Global warming potentials (see Table 14)
ERD_p	=	Emission reduction for each GHG (p) (see prior equation)

6.3 Physical Activity benefits

Physical activity benefits are calculated for both bicycle and pedestrian projects and are reported in the total increase in Marginal Metabolic Equivalent of a Task (MMET). Metabolic Equivalent Tasks (METs) is a method for combining time spent in activities of different physical intensity. One MET is the amount of energy used while sitting quietly and MMETs only consider the marginal activity over and above rest (sitting quietly). This tool uses METs for walking and bicycling from the 2011 compendium of physical activities (Ainsworth et al., 2011) based on travel speed and subtracts one from each value resulting in a table of MMETs (Table 15). We use the range in MMETs by speed of each activity to report the range in expected increases in physical activity from a given project.

Table 15 Marginal Metabolic Equivalent of Task for Walking and Bicycling by Speed

	Walking			Bicycling		
	Low	Average	High	Low	Average	High
Speed (miles per hour)	1.5	3.0	4.5	5.5	10.0	15.0
MMET per hour	2.0	2.5	7.0	2.5	4.8	9.0

The increase in MMETs from the given project intervention is calculated from three categories of the active travel increase: car shift, induced travel, and shift from other modes. This is because the tool assumes route shift does not change trip distance and thus does not add to physical activity (see Section 5.2 for discussion about the potential for future changes to this assumption). The equation used to calculate MMETs is:

$$Increase\ in\ daily\ MMET_m = ATI_m * \frac{M_m}{S_m}$$

where:

ATI_m	=	Active travel increases excluding route shift fraction (see section 5)
M_m	=	MMET per hour
S_m	=	Speed in miles per hour

6.3 Safety Benefits

The tool considers three types of project-level safety benefits: crash reduction, injury reduction, and death reduction. Reductions in car speeds and crime are reported in the general benefits section because existing traffic speeds and crime are currently not included in this tool at the project level. Future revisions to the tool should consider incorporating base speed and crime levels to calculate project-specific reductions. Table 16 shows the bicycle and pedestrian project elements that were found in the literature review to produce quantitative safety benefits. A low, average, and high estimate is provided for each project element and the average effect imputed from the midpoint of the range of the studies if no meta-analysis for the given element was found, and when only one average was found, the range was assumed to be 50% above and below the mean with an upper constraint at 99%.

Table 16: Projects Elements with Quantitative Effects on Bicycling Safety

Project Element	Mode	Class	Outcome	Percent Decrease		
				Low	Average	High
Bicycle boulevard	Combined	Roadway	Crashes	2%	5%	8%
Conventional/Buffered Bicycle Lane	Combined	Roadway	Crashes	5%	36%	66%
			Injuries	60%	69%	78%
			Deaths	10%	46%	81%
Crossing islands	Pedestrian	Intersection	Crashes	23%	37%	50%
			Injuries	34%	47%	59%
			Deaths	28%	47%	65%
Curb Extensions	Pedestrian	Intersection	Crashes	-9%	-3%	3%
			Injuries	4%	6%	9%
			Deaths	10%	11%	14%
Flashing beacons	Pedestrian	Intersection	Crashes	43%	51%	57%
			Injuries	46%	53%	59%
			Deaths	40%	53%	65%
Lane Narrowing	Combined	Roadway	Crashes	0%	6%	11%
			Injuries	43%	51%	57%

			Deaths	21%	41%	61%
Lighting	Combined	Intersection	Crashes	32%	44%	55%
			Injuries	22%	27%	32%
			Deaths	33%	66%	99%
		Roadway	Crashes	32%	44%	55%
			Injuries	22%	27%	32%
			Deaths	33%	66%	99%
Protected Bicycle Lane	Bicyclist	Roadway	Crashes	30%	60%	90%
			Injuries	41%	70%	99%
			Deaths	36%	70%	99%
Raised crossings	Pedestrian	Intersection	Crashes	20%	40%	60%
			Injuries	12%	24%	36%
			Deaths	25%	50%	75%
Road diets	Combined	Roadway	Crashes	19%	33%	47%
			Injuries	30%	43%	56%
			Deaths	24%	43%	62%
Roundabouts	Combined	Intersection	Crashes	43%	51%	57%
			Injuries	45%	65%	85%
			Deaths	35%	44%	52%
Shared Streets	Combined	Roadway	Crashes	25%	50%	75%
			Injuries	36%	60%	84%
			Deaths	30%	60%	90%

The effects sizes in Table 16 only include safety benefits for people walking and riding bikes. Future revisions to this tool should consider including effects on people in cars as many interventions for walking and bicycling focus on speed management which is known to also improve safety for drivers (Grembek et al., 2020).

A primary challenge for calculating safety benefits for active transportation projects are uncertain exposures and crashes. Both exposure and crashes are context sensitive, traffic crashes are highly infrequent, and data is underreported (Winters and Branion-Calles, 2017). These issues make any active travel safety calculations difficult. Future research is needed to estimate reliable safety performance functions (statistical equations of risk) for active travel in California. When those functions are developed, this tool should revise the safety benefits calculation. Until then, the tool estimates existing crashes from user provided local data (if available) and/or 5 years of SWITRS crash data statewide. This approach is consistent with the idea of systemic risk,[15] although crude. The assumption in this tool is that when 5 years of local data is available it is the best estimate for existing crashes and crash outcomes. When that data is not available, statewide data can be used to estimate crashes and crash outcomes crudely from a systemic perspective (see Section 6.3.2).

The tool uses a modified equation from Elvik and Bjørnskau (2017) for estimating crashes ignoring the covariate term, car volume term, and using slightly different notation:

$$crashes = e^{\alpha} * V^{p}$$

where:

α	=	Constant to be estimated by a regression (e.g., poisson, gamma-poisson)
V	=	Volume of active travel
p	=	Parameter to be estimated by the same regression

Notably the above equation does not include car volume (as suggested by Elvik and Bjørnskau (2017), because car volumes are not available at the entire network level. Future versions of this tool should consider equations to predict car volume or ask the user to submit car volumes for their project. Since we did not conduct a study to estimate regressions of safety (a worthwhile future study, but a challenge given the 4.5 million network roads in this dataset), we borrowed meta-analysis regression coefficients for active travel volume from Elvik and Bjørnskau (2017), and used SWITRS crash data to solve for the missing alpha parameter. Because SWITRS has more than 30,000 crashes for bicyclists and pedestrians from the past 5 years, we attempted to account for the lack of car volume and other missing contextual covariates by calculating a series of alpha parameters by mode, outcome, location, classified active travel volume, and functional road class (See Appendix A). The series of alpha parameters and the use of local project-specific active travel volumes provides an estimate of local crashes which can be used to calculate baseline safety.

To communicate safety benefits, the tool reports (1) changes in crash outcomes, (2) before project crash rates and (3) after crash rates. The general equations the tool uses for calculating safety benefits at the annual level are as follows:

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[15] https://safety.fhwa.dot.gov/systemic/

$$EC_{moj} = \begin{cases} \dfrac{UI_{moj}}{y} & if\ y \geq 5 \\ \displaystyle\sum_f \sum_v \frac{UI_{moj}}{y} * \left(\frac{y}{5}\right) + \left(1 - \left(\frac{y}{5}\right)\right) * CC_{mojvf} & if\ 5 > y > 0 \\ \displaystyle\sum_f \sum_v CC_{mojvf} & if\ y = 0\ |\ NA \end{cases}$$

$$CC_{mojvf} = e^{\alpha_{mojvf}} * L_{vf} * V_{mj}{}^{p}$$

$$NC_{moj} = \sum_f \sum_v \sum_{i=1}^{n} e^{\alpha_{mojvf}} * L_{vf} * \left(V_{mj} + V_{mj} * E_i * \frac{N_i}{L} * I\right)^{p} * CRF_{moji}$$

$$Crash\ Change_{mo} = \sum_j NC_{moj} - EC_{moj}$$

$$Before\ crash\ outcomes\ per\ 1000\ volume_{mo} = \left(\sum_j \frac{EC_{moj}}{V_{mj}}\right) * 1000$$

$$After\ crash\ outcomes\ per\ 1000\ volume_{mo} = \left(\sum_j \frac{EC_{moj}}{V_{mj}}\right) * 1000$$

where:

m	=	Mode index: 1=bicycling, 2=walking, 3=bicycling and walking combined
o	=	Outcome index:1=crash, 2=injury, 3=death
j	=	Location type index: 1=intersection, 2=roadway
v	=	Volume index: 1 = low volume, 2 = medium volume, 3 = high volume
f	=	Functional class index: 1 = major road, 2 = minor road, 3 = local road
y	=	Years of data provided by user
UI_{mo}	=	User input crashes
CC_{mojvf}	=	Crashes by system classes (See appendix A)
EC_{mojvf}	=	Estimated existing crash outcomes
NC_{mojvf}	=	Estimated new crash outcomes
α_{mojvf}		Constant representing the expected crashes (see section 6.3.2)
V_{mj}		Volume of active travel (see section 6.3.1)
E_i	=	Percentage (fractional) increase in active travel due to the project element (*i*)
N_i	=	Length or count of the project element (*i*)
L	=	Total project length or count
I	=	Improvement type *I* = 1 for New and Significant Upgrade *I* = 0.1 for Retrofit or Maintenance

p	=	Power representing the safety-in-numbers effect[16]
i	=	1, …, n corresponding to project elements (i)
n	=	Total number of project elements (i) selected by the user that influence safety

The following sections provide the detailed steps for producing volumes for active travel (V_{mj}) and the missing constant from the crash model (α_{mojvf}).

6.3.1 Estimate existing bicycle and pedestrian volumes

Bicycle volumes on roadways (links) and pedestrian crossing volumes at intersections (nodes) are estimated directly from the models of existing active travel (see Section 4). Since bicycling volumes are predicted on roadways (links), bicycling volumes at intersections need to be interpolated. The tool assumes that each bicyclist travels through the adjoining intersections and since turn directions are unknown, it assumes half of the roadway volume is expected to cross through the adjoining intersections (i.e., each bicyclist passes through and is counted on two adjoining roadways).

Pedestrian volume is predicted at intersections (nodes). This prediction is of all intersection crossing volumes (but not right turns since pedestrians do not cross the intersection to turn right). Leaving out right turns at intersections may be appropriate for walking since right turning pedestrians have little traffic exposure risk. However, when interpolating pedestrian volume from intersections to adjoining roadways, the tool assumes all pedestrians use two adjoining roadways and so doubles the volume and distributes that volume equally across adjoining roadways.

Both interpolation methods are crude ways of distributing volume from nodes to links and links to nodes. Future revisions to this tool should consider more behaviorally sensitive interpolation techniques.

6.3.2 Estimating Existing Crashes and Alpha Parameters

Estimates for project level crashes are optionally provided through user input. This is because users may have local data of crashes, injuries, and deaths that consider the details of the local context. If a user provides 5 years of data, the user provided data is used to calculate annual crashes, injuries, and deaths for bicycling and walking at both intersections and roadways. If no

[16] The safety-in-numbers power effect of 0.5 has been stable across many studies for walking and bicycling (Elvik and Bjørnskau, 2017)

crash data is provided, crashes are estimated from a table of classes of roadways (Appendix A). If some but less than 5 years of crash data are provided, a weighted average (based on number of years of data) is used to estimate crashes, injuries, and deaths.

To calculate crashes and crash outcomes in Appendix A, the entire network of roadways and intersections was reclassified by mode, outcome, location, classified active travel volume, and functional road class (See Appendix A). Functional road class was determined by grouping OSM tags (Table 17) and classifying volume estimates. That reclassified network was spatially joined to 5 years (2015-2019) of SWITRS bike and pedestrian geocoded crash data based on the nearest roadway (for non-intersection crashes) or intersection (for intersection crashes) to the road network. The crashes and crash outcomes were summed for each class to determine Appendix A values which were joined to every network link and node.

Table 17. OSM Functional Roadway Reclassification

OSM Roadway Classification	Tool Reclassification
motorway	Major Road
motorway_link	
trunk	
trunk_link	
primary	
primary_link	
secondary	Minor Road
secondary_link	
tertiary	
tertiary_link	
unclassified	
residential	Local Road
path	
living_street	

This approach has many limitations. Mostly importantly, it is entirely deterministic based on crash data and does not account for the relationships between variables and crashes. A better approach is to estimate a model to account for other contextual factors that are known to contribute to crashes (Chen et al., 2020). Because of the limitation in this current approach, and because crash risk is highly localized, users are encouraged to provide their own data to be used to define existing risk. Once crashes, injuries, and deaths are estimated and the active travel volumes are summarized for each row in Appendix A, the alpha parameters are solved from the original crash equation:

$$crashes = e^{\alpha} * V^{p}$$

$$\alpha = \ln\left(\frac{crashes}{V^{p}}\right)$$

where:

α	=	Solved by algebra
V	=	Volume of active travel
p	=	0.5 (assumed from Elvik and Bjørnskau (2017))
crashes	=	Estimated from Appendix A

7 General Benefits

Many benefits from active transportation projects are difficult to quantify due to a lack of research, dependence on data that is unavailable, or a lack of consensus about how to measure them. However, ignoring the hard to quantify and hard to describe benefits understates the impact of active transportation projects on communities. In this tool, we provide general benefits for each project based on the accompanying literature review.[17] Where quantitative benefits are observed but difficult to apply to specific projects, they are presented as a general unified statistic. Actual benefits are likely to vary from project to project so these descriptions should be cautiously considered. The quantitative, yet general outcomes in the tool are some of the possible next project-level benefits to include in future versions of the tool because they have some evidence of quantitative improvement, yet for a variety of reasons we could not estimate them at the project level (e.g., speed reductions, and crime reductions).

Many other benefits are even less certain in the literature yet have compelling theoretical or anecdotal evidence for support. These benefits we provide in qualitative terms based on the literature review. Future research is needed to quantify the magnitude of these benefits by project elements. Programs designed to increase walking and bicycling often fall under this category. Outcomes from programs are difficult to measure, often are not measured at all, and have had little attention from researchers in comparison to infrastructure investments. Evidence suggests implementing programs and infrastructure in combination are likely to achieve greater benefits

[17] https://activetravelbenefits.ucdavis.edu/litreview

(Pucher et al., 2010), so qualitative statements in this tool communicate this and other potential synergies.

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Appendix A. Estimated Crash Outcomes and Alpha Parameters

Location	Mode	Exposure Class	Functional Class	Prevalence (count)	Average Daily Volume (bike/ped)	Crashes/ intersection/ year	Injuries/ intersection/ year	Deaths/ intersection/ year	α Crash	α Injury	α Death
Intersection	Bike	Low	Local road	186	4.9	0.208	0.206	0.001	-2.36	-2.37	-7.63
			Minor road	541	4.8	0.218	0.213	0.006	-2.31	-2.34	-5.98
			Major road	205	5.8	0.215	0.208	0.007	-2.42	-2.45	-5.86
		Medium	Local road	472	42.3	0.211	0.211	0.000	-3.43	-3.43	-13.39
			Minor road	1744	43.9	0.225	0.221	0.003	-3.38	-3.40	-7.60
			Major road	746	55.7	0.232	0.227	0.004	-3.47	-3.49	-7.46
		High	Local road	1689	161.2	0.216	0.215	0.001	-4.07	-4.08	-9.39
			Minor road	8550	170.8	0.246	0.244	0.002	-3.97	-3.98	-8.77
			Major road	5010	168.3	0.263	0.260	0.003	-3.90	-3.91	-8.53
	Walk	Low	Local road	510	215.1	0.218	0.213	0.005	-4.21	-4.23	-7.89
			Minor road	2110	222.1	0.241	0.231	0.010	-4.12	-4.17	-7.31
			Major road	880	234.4	0.261	0.242	0.019	-4.07	-4.15	-6.70
		Medium	Local road	636	643.8	0.224	0.219	0.004	-4.73	-4.75	-8.73
			Minor road	2605	645.8	0.251	0.241	0.010	-4.62	-4.66	-7.83
			Major road	1448	646.8	0.275	0.263	0.012	-4.53	-4.57	-7.68
		High	Local road	1304	1534.2	0.235	0.232	0.003	-5.11	-5.13	-9.36
			Minor road	6257	1731.0	0.303	0.296	0.007	-4.92	-4.95	-8.75
			Major road	3849	1636.1	0.329	0.320	0.009	-4.81	-4.84	-8.40

Location	Mode	Exposure Class	Functional Class	Prevalence (miles)	Average Daily Volume (bike/ped)	Crashes/ mile/ year	Injuries/ mile/ year	Deaths/ mile/ year	α Crash	α Injury	α Death
Roadway	Bike	Low	Local road	262173.8	9.1	0.004	0.004	0.000	-6.66	-6.68	-10.33
			Minor road	37340.8	9.3	0.020	0.019	0.001	-5.03	-5.06	-8.48
			Major road	12273.1	9.0	0.027	0.026	0.001	-4.70	-4.74	-8.03
		Medium	Local road	66892.1	85.6	0.016	0.016	0.000	-6.34	-6.36	-10.63
			Minor road	7836.1	76.1	0.077	0.076	0.001	-4.73	-4.75	-9.13
			Major road	4256.9	84.0	0.089	0.087	0.002	-4.64	-4.66	-8.49
		High	Local road	61404.9	235.0	0.011	0.011	0.000	-7.20	-7.21	-12.27
			Minor road	8911.5	252.8	0.106	0.105	0.001	-5.02	-5.02	-9.76
			Major road	6063.0	244.1	0.093	0.092	0.002	-5.12	-5.14	-9.18
	Walk	Low	Local road	80943.7	267.6	0.010	0.009	0.000	-7.44	-7.48	-10.68
			Minor road	107698.8	286.6	0.011	0.010	0.001	-7.31	-7.43	-9.56
			Major road	10790.2	288.2	0.066	0.053	0.013	-5.56	-5.77	-7.21
		Medium	Local road	53183.8	801.9	0.013	0.013	0.000	-7.69	-7.72	-11.21
			Minor road	97944.6	806.6	0.012	0.011	0.001	-7.80	-7.88	-10.41
			Major road	8374.4	820.2	0.109	0.094	0.015	-5.57	-5.72	-7.52
		High	Local road	31808.4	2087.6	0.020	0.019	0.001	-7.76	-7.78	-11.39
			Minor road	60626.6	2306.2	0.021	0.020	0.001	-7.74	-7.79	-10.68
			Major road	9746.2	2268.6	0.101	0.090	0.011	-6.16	-6.27	-8.39