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16. ABSTRACT

Caltrans is considering performance measures that can be used to evaluate the quality of the bicycling experience on the state highway system. The purpose of this research is to recommend the best methodology to use in California as a quantitative measurement for how well the roads support bicycling. We identified two widely used performance measures, Highway Capacity Manual bicycle level of service and level of traffic stress, for evaluation, and developed time cost estimates for applying the measures to the state highway system. In addition, we performed a pilot study to test a proof of concept for a customized California-specific performance measure, incorporating the superior elements of established measures, accounting for the variety of features present on California roads, and taking advantage of existing data sources. We used a latent class choice model based on a bicyclist user experience survey to show the different facility preferences for different types of riders. Due to the limited validity of using existing performance measures for the California state highway system, we recommend further development of a California-specific performance measure.

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Performance Measures for Bicycle Suitability on the State Highway System

Final Report

Prepared by the

UC Berkeley Safe Transportation Research and Education Center

for the

California Department of Transportation

and the

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August, 2016

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Table of Contents

Disclaimer Statement 1

Acknowledgments 3

List of Figures 5

List of Tables 6

Executive Summary 7

1 Introduction 8

2 Existing Performance Measures 9

2.1 Background 9

2.2 Data Requirements 10

2.3 Data Collection 11

2.3.1 TASAS Data Availability 11

2.3.2 TASAS for Bikes 12

2.3.3 Data Collection Challenges 13

2.4 Time Cost Estimates 14

2.4.1 Step 1. Classify the pilot routes by Roadway Classification 15

2.4.2 Step 2. Identify the variables used in time cost estimation for bicycle performance evaluation 17

2.4.3 Step 3. Summarize the total time cost for each route segments identified in the classification 20

2.4.4 Step 4. Reclassify the TASAS highway segment records using CA HSIS roadway classification definition 20

2.4.5 Step 5. Summarize the mileage for each class of the roadway for the entire State Highway System 20

2.4.6 Step 6. Calculate the total time cost estimate 21

2.4.7 Step 7. Split the roadway classes into subgroups according to the width of the treated shoulder 21

2.4.8 Step 8. Summarize the time cost for each performance measure 21

3 Pilot California-specific Performance Measure 26

3.1 Data Collection 27

3.1.1 Video Data Collection 27

3.1.2 Survey Development 30

3.1.3 Survey implementation ... 31
3.2 Summary of survey results ... 31
3.2.1 Online survey ... 31
3.2.2 In-person survey ... 32
3.3 Pilot Model ... 36
3.3.1 Methodology ... 37
3.3.2 Model Framework ... 39
3.3.3 Estimation Results ... 41
3.3.4 Class Specific Analysis ... 43
3.3.5 Next Steps ... 44
4 Evaluation of Performance Measures ... 47
4.1 Applying BLOS ... 47
4.2 Applying LTS ... 47
4.3 Comparison ... 48
5 Conclusion ... 54
6 References ... 55
7 Appendix A: TASAS variables and values ... 58
8 Appendix B: Time cost to link to TASAS ... 62
8.1 Steps ... 62
8.2 Time cost for the test ... 62
8.3 Time cost for SHS ... 62
9 Appendix C: Survey ... 63

List of Figures

Figure 1. Procedure and challenges for time cost estimation ... 15
Figure 2. Age distribution of online survey respondents ... 32
Figure 3. Gender distribution of online survey respondents ... 32
Figure 4. Typical bicycle trip purposes of online survey respondents ... 32
Figure 5. Themes (number of references) of responses to bicycle simulation videos ... 33
Figure 6. Screen capture from the video of a two-lane road near a regional park in Berkeley, CA ... 35
Figure 7. LCCM framework ... 40
Figure 8. Favorable videos for each class ... 44

Figure 9. Scatter plot of survey ratings and BLOS scores 50
Figure 10. Miles Ave. in Oakland received the best survey rating 51
Figure 11. Tunnel Rd. from Hiller to Vicente received the second best survey rating 51
Figure 12. Scatter plot of survey ratings and LTS scores 52
Figure 13. Bubble plot of BLOS and LTS scores 53

List of Tables

Table 1. Variables used in BLOS and LTS measures 10
Table 2. TASAS variables relevant to bicycling experience 11
Table 3. Potentially relevant variables collected from the TASAS for Bikes study 12
Table 4. Classification of pilot routes 16
Table 5. Variables and surrogates used for the time cost estimation 18
Table 6. Re-classification of TASAS highway segments using CA HSIS roadway classification 20
Table 4. Time cost for BLOS measurements 23
Table 5. Time cost for LTS measurements 24
Table 4. Roads included in video data collection 28
Table 5. Video data collection categories 29
Table 6. Estimation Results 42
Table 7. Pearson's correlation coefficients for performance measure scores and survey ratings 48
Table 8. TASAS variables potential relevant to bicycling and their values 58

Executive Summary

Caltrans is considering performance measures that can be used to evaluate the quality of the bicycling experience on the California State Highway System. The goal of this study was to identify an appropriate and feasible performance measure for bicycle suitability.

We identified two widely used performance measures, Highway Capacity Manual bicycle level of service (BLOS) and level of traffic stress (LTS), for evaluation. BLOS is an empirically derived measure with intense data requirements, while LTS is based on expert opinion, but is more simple to apply and intuitive to interpret. First, we evaluated the level of effort required for data collection. The time cost estimates for applying the measures were similar, 4,300 hours for BLOS and 4,400 hours for LTS, but the BLOS estimates represent the time required assuming the availability of motorized traffic flow and running speed from a traffic study, which was outside the scope of this study and may require additional data collection efforts.

In addition, we performed a pilot study to test a proof of concept for a customized California-specific performance measure, incorporating the superior elements of established measures, accounting for the variety of features present on California roads, and taking advantage of existing data sources. We used a latent class choice model based on a bicyclist user experience survey to show the different facility preferences for different types of riders.

Finally, comparison of BLOS, LTS, and user survey ratings of 38 road segments highlighted the inability of existing performance measures to capture the impact of newer bicycle facility designs, such as protected bicycle lanes with physical barriers. BLOS was weakly correlated with the survey ratings ($\rho=0.29$), while LTS had a moderate correlation ($\rho=0.60$).

Due to the limited validity of using existing performance measures for the California state highway system, we recommend further development of a California-specific performance measure.

1 Introduction

Caltrans, as well as other agencies, are making an effort to design and maintain facilities that are suitable to address the needs of road users across all modes. This includes efforts to accommodate bicycles, which pose low emissions of pollutants, noise and collision risks to other road users. The California state highway system (SHS) contains more than 10,000 miles of roadway that are accessible to bicycles. Ninety percent of the bicycle-accessible network is rural highways, mostly 2-lane roads. This huge network necessitates adoption of an approach to evaluate how “shareable” or “bicycle friendly” roads are, that is feasible to apply at such a scale, while also capturing the meaningful variation among facilities.

To address this need, Caltrans is considering performance measures that can be used to objectively assess the quality of the bicycling experience on the California SHS. A performance measure of this type, commonly referred to as a bicycle level of service (BLOS), establishes a quantitative association between objective attributes of the roadway environment and subjective measures of the cyclist’s experience. It can be used to prioritize infrastructure improvements for bicyclists and identify continuous networks suitable for bicycle travel. Caltrans is aware that other states use several different methodologies, including various versions of BLOS, bicycle level of comfort (BLOC), level of traffic stress (LTS), bicycle compatibility index (BCI), and adhoc measures.

In light of this, the overarching goal of this research is to recommend the best methodology to use in California as a quantitative measurement for how well the roads support bicycling. To achieve this goal, this study would: (i) evaluate the time cost of applying existing performance measures to the California SHS; and (ii) identify or develop a valid, practical, and feasible performance measure for bicycle suitability.

This technical report describes the tasks and activities that were conducted to accomplish the study objectives. Chapter 2 provides some background about existing bicycle performance measures, and documents the data requirements, data collection efforts, and time cost estimates of two widely used performance measures. Chapter 3 describes the California-specific performance measures that was developed under this study, along with the steps taken to develop such a model based on a pilot survey, and the practical applications of such a performance measure. Chapter 4 provides a comparison on how different performances measures rate a range of different roadways. Chapter 5 discusses the conclusions and recommendations of the study.

2 Existing Performance Measures

2.1 Background

Researchers have developed a number of BLOS-type performance measures over the past 20 years. Many of these measures use the name bicycle level of service, or BLOS, and a scale of A through F to parallel the performance measure used for automobiles, level of service (LOS) (Dixon 1995, Landis et. al. 1997, Jensen 2007, NCHRP 2008, and HCM 2010). A commonly referenced BLOS measure was developed for the Highway Capacity Manual, as a counterpart to measures for pedestrians, transit, and automobiles, which combine to be called multi-modal level of service (MMLOS) (HCM 2010). Bicycle compatibility index (BCI) (Harkey et al. 1998) and the HCM BLOS both use regression models with dependent variables based on user response to videos of roadway segments. The ranges of result values for each regression are matched with corresponding A through F values to rate the segment. While the ratings may be convenient for traffic engineers or planners who are used to working with LOS, they are arbitrary and it is difficult to determine what rating constitutes an acceptable environment for bicyclists. Additionally, the high constant in the regression equation for the HCM BLOS makes it nearly impossible to obtain a rating of A or B (Huff and Liggett 2014).

LTS has gained popularity, especially among local jurisdictions, for its ease of application and interpretation. Rather than using an empirically developed model, LTS ratings are based on expert opinion of the study authors (Mekuria et al. 2012). The measure is applied using tables for types of roadways (i.e. roads with a bike lane and no parallel parking) and each stress level (1 through 4) is defined by a set of thresholds where all the minimum values must be met. This system, while simple to apply, does not allow for combinations of attribute values that could potentially produce comparable comfort for bicyclists.

One very appealing aspect of the LTS measure is the rating system they use for roadways, which is based on the Portland typology of cyclists developed by Geller (2009). Each stress level assigned to a roadway corresponds to the minimum level cyclist from the typology that would be comfortable riding on the road. The typology includes four types: “strong and fearless,” “enthused and confident,” “interested but concerned,” and “no way no how.” The first two types correspond to LTS ratings 3 and 4, whereas LTS 1 and LTS 2 divides the “interested but concerned” type among children and adults, respectively. A road segment with a value of LTS4 would be suitable for only the strongest riders, who are comfortable riding in fast moving or heavier traffic without designated bicycle facilities. A rating of LTS2 corresponds to a road with facilities or conditions that would be suitable for most inexperienced riders, as well as the more experienced riders in the “strong and fearless” and “enthused and confident” categories.

HCM BLOS, heretofore referred to as BLOS, was selected for evaluation in this study because of its prominence as the recommended bicycle performance measure in HCM 2010. LTS was selected because of its popularity among local communities and transportation consultants in California.

2.2 Data Requirements

BLOS has considerably greater data requirements than LTS, but both measures cover the themes of bicycle facilities, space for bicycles, street width, and vehicle speed. The variables used for each measure are shown in Table 1. BLOS requires data on vehicle and truck volumes and pavement quality, as well as greater detail on bicycling space. In particular, it accounts for the effective bikeway width as determined by the width of the outside lane and the shoulder. Neither measure, however, can capture the effect of a physical barrier between a bike lane and traffic because there is no variable input related to that attribute. The vehicle flow data for BLOS are meant to be derived from a traffic analysis study, like that required for the automobile LOS measure. The method to collect on-street parking occupancy data is open to interpretation and might be inconsistent across regions, but would also typically require field work. The LTS data can mostly be collected remotely, using Google imagery resources. Bike lane blockage can be replaced by a proxy of whether the road is in a commercial district, but is meant to be based on a planner's expert knowledge of the area.

Table 1. Variables used in BLOS and LTS measures

Explanatory Variable Theme	BLOS Variable	LTS Variable
	Segments	
Bicycle Space	Effective width of outside through lane	Bike lane width
		Presence of bike lane
	Width of paving between outside lane stripe and the edge of pavement	
	Width of outside through lane plus paved shoulder	
Parking	Proportion of on-street parking occupied (decimal)	Presence of parking lane
		Bike lane blockage (rare/frequent)
Street Width	Number of through lanes on the segment in the subject direction of travel (ln)	Width of street (number of lanes)
Vehicle Volume	Mid-segment demand flow rate (veh/h)	
	Percent heavy vehicles in the mid-segment demand flow rate (%)	

Explanatory Variable Theme	BLOS Variable	LTS Variable
Vehicle Speed	Motorized vehicle running speed (mi/h)	Speed limit or prevailing speed
Other	Effective width as a function of traffic volume Pavement condition rating	
	Intersections	
Bicycle Space	Total width of outside through lane and bike lane (if present)	Presence of pocket bicycle lane
Intersection Dimensions	Crossing distance, the width of the side street (including auxiliary lanes and median) Total number of through lanes on the approach to the intersection	Length of right turn lane
Intersection Control		Presence of signal
Median		Presence of median

2.3 Data Collection

This section describes the required data collection for bicycle performance measures. The TASAS Data Availability section describes the variables from the Traffic Accident Surveillance and Analysis System (TASAS) database that could be used for calculation of BLOS or LTS and those that are otherwise relevant to bicyclist user experience. The TASAS for Bikes section describes the additional relevant variables that were collected for the TASAS for Bikes study (Zhang et al. 2016).

2.3.1 TASAS Data Availability

The TASAS database highway and intersection tables contain a number of potentially relevant explanatory variables, many of which are similar to variables used in other measures. Table 2 shows these TASAS variables categorized by theme.

Table 2. TASAS variables relevant to bicycling experience

Variable Theme	Variable Name	Description
	Segment	
Bicycle Space	thy_lt_o_shd_trt_width_amt / thy_rt_o_shd_trt_width_amt*	Left/right outside shoulder treated width (ft)
Street Width	thy_lt_lanes_amt / thy_rt_lanes_amt*	Number of lanes, left/right side
Vehicle Volume	thy_adt_amt	Annual average daily traffic (AADT) amount

Vehicle Speed	thy_design_speed_amt	Design speed
Other	thy_highway_access_code	Type of highway, including freeway, expressway, or conventional highway
	thy_terrain_code	Type of terrain surrounding road
	thy_highway_access_code	Access control
	thy_lt_spec_features_code / thy_rt_spec_features_code	Road bed features, left/right side
	Intersection	
Intersection Dimensions	inx_main_lanes_amt*	# of lanes on main street
	inx_cross_lanes_amt*	# of lanes on crossing street
Turn Lanes	inx_main_left_channel_code	Mainline left turning features
	inx_main_right_channel_code	Mainline right turning features
	inx_cross_left_channel_code	Cross-street left turning features
	inx_cross_right_channel_code	Cross-street right turning features
Vehicle Volume	inx_mainline_adt	Mainline AADT
	inx_xstreet_adt	Cross-street AADT
	inx_control_code	Traffic control type
Median	thy_median_type_code	Median type

* Variables that can be used directly to calculate BLOS or LTS

2.3.2 TASAS for Bikes

Although TASAS contains no data explicitly related to bicycles, SafeTREC has performed a parallel study to develop a database structure for bicycle infrastructure and volume data as an extension to TASAS and to evaluate the level of effort to collect the data (Zhang et al. 2016). Several variables that are potentially relevant to a bicycle performance measure were included in this study.

Table 3. Potentially relevant variables collected from the TASAS for Bikes study

Variable Theme	Variable Name	Description
	Segment	
Bicycle Space	Bikeway type	
	Bikeway Width*	
	Bikeway barrier type	Barriers between vehicle lane and bike lane.
Roadway Features	Type of lane adjacent to outside vehicle lane	

Variable Theme	Variable Name	Description
	Width of outside lane*	
	Speed reducing / traffic calming measure presence	
Parking	Vehicle parking presence*	
	Maximum number of parking spaces*	
	Vehicle parking type	
Bicycle Markings	Pavement marking types	
	Pavement marking color	
	Signage presence	
Other	Average gradient	
	Intersection	
Signal	Bicycle signal presence	
Turning lanes	Bike lane on the left side of the right turn only lane	
	Bike lane on the right side of the left turn only lane	
	Bike waiting area/box/pocket	
	Weaving area presence	
	Number of right turn only lanes	
	Number of left turn only lanes	
	Vehicle left turn pocket presence	
	Vehicle right turn pocket presence	
	Vehicle right turn split lane control	
	Number of lanes on the cross street	

* Variables that can be used directly to calculate BLOS or LTS

2.3.3 Data Collection Challenges

There are three variables required for BLOS, midsegment demand flow rate, percent heavy vehicles in the midsegment demand flow rate, and motorized vehicle running speed, that are neither available in TASAS nor reasonable to gather remotely using the collection methods from the TASAS for Bikes study (Zhang et al. 2016). The recommended method in HCM 2010 for collecting these variables is a traffic study, including field data collection, like that used to determine automobile LOS. This requirement adds a significant extra burden to the calculation of BLOS, given the scale of effort necessary to apply it to the SHS.

2.4 Time Cost Estimates

We used time cost data collected by a separate Caltrans study (Zhang et al. 2016) to produce time-cost estimates (for variables that do not require a traffic study) for applying BLOS and LTS to the SHS. Data were collected along 66.7 miles of state highways selected to capture variation in several TASAS variables—population code, AADT, design speed, number of lanes, and shoulder width. The procedure for the time cost estimation is shown in Figure 1 and the details for each step are described below.

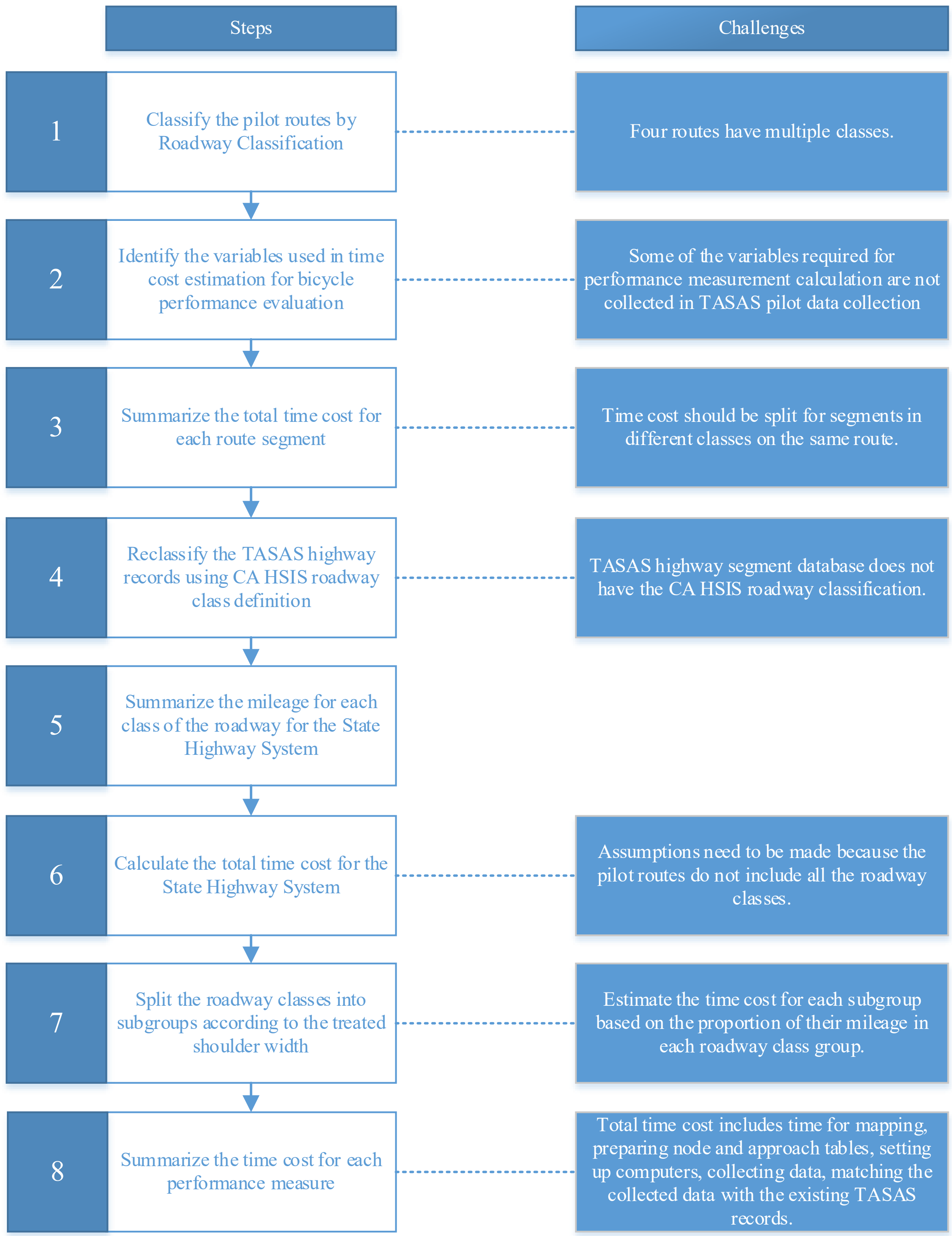

Figure 1. Procedure and challenges for time cost estimation

2.4.1 Step 1. Classify the pilot routes by Roadway Classification

This classification is determined by California Highway Safety Information System (CA HSIS), also described in Table 6. Roadway features considered in the classification include urban or rural, divided or un-divided, number of lanes, and freeway or non-freeway. The classification is shown in Table 4. It should be noted that, during the classification, four routes (the last four in Table 4) have multiple segments in different classes. They should be split for the future time cost estimation.

Table 4. Classification of pilot routes

<table>
<tr><th>Route</th><th>County</th><th colspan="2">Name of Route</th><th>Roadway Class</th><th>Miles</th></tr>
<tr><td>1</td><td>SLO</td><td colspan="2">21st St to Hinds Ave</td><td>3</td><td>3.59</td></tr>
<tr><td>49</td><td>ED</td><td colspan="2">Lincoln Hwy (Jct Rte 50) to Shanghai Way Rt</td><td>3</td><td>1.209</td></tr>
<tr><td>1</td><td>ORA</td><td colspan="2">7th St Rt to Warner Ave</td><td>4</td><td>4.989</td></tr>
<tr><td>1</td><td>ORA</td><td colspan="2">Riverside Ave to Newland St</td><td>4</td><td>3.76</td></tr>
<tr><td>35</td><td>SF</td><td colspan="2">Harding Rd Rt to 20th Ave Rt</td><td>4</td><td>1.74</td></tr>
<tr><td>123</td><td>ALA</td><td colspan="2">37th St Rt to Ashby Ave (Rte 13)</td><td>4</td><td>1.883</td></tr>
<tr><td>273</td><td>SHA</td><td colspan="2">Bruce St Lt to Latona Rd Rt</td><td>4</td><td>4.3</td></tr>
<tr><td>1</td><td>MEN</td><td colspan="2">Usal Rd to Hales Grove</td><td>8</td><td>5.76</td></tr>
<tr><td>1</td><td>SLO</td><td colspan="2">San Geronimo Rd to Harmony Valley Rd</td><td>8</td><td>6.65</td></tr>
<tr><td>58</td><td>SLO</td><td colspan="2">Park Hill Rd to Huer Huero Rd Rt</td><td>8</td><td>4.93</td></tr>
<tr><td>84</td><td>ALA</td><td colspan="2">Vallecitoc Rd at Old Hwy to Rubyhill Lt/Kalthoff Rt</td><td>8</td><td>4.505</td></tr>
<tr><td>84</td><td>ALA</td><td colspan="2">Old Niles Canyon Rd to Main St</td><td>8</td><td>2.85</td></tr>
<tr><td>130</td><td>SCL</td><td colspan="2">Kincaid Rd to Mt Hamilton</td><td>8</td><td>5.262</td></tr>
<tr><td rowspan="5">13</td><td rowspan="5">ALA</td><td rowspan="5">Hiller Dr/ Tunnel Rd to Mabel St</td><td>HILLER DR/TUNNEL RD to the intersection at CLAREMONT AVE</td><td>3</td><td>0.8</td></tr>
<tr><td>CLAREMONT AVE to the intersection at ELMWOOD COURT LT</td><td>5</td><td>0.12</td></tr>
<tr><td>ELMWOOD COURT LT to the intersection at TELEGRAPH AVE</td><td>3</td><td>0.7</td></tr>
<tr><td>TELEGRAPH AVE to the intersection at OTIS ST RT</td><td>5</td><td>0.66</td></tr>
<tr><td>OTIS ST RT to Mabel St</td><td>4</td><td>0.75</td></tr>
<tr><td rowspan="2">36</td><td rowspan="2">LAS</td><td rowspan="2">Pratville Dr Lt to East</td><td>Pratville Dr Lt to N Mesa St Lt/S Mesa St Rt</td><td>5</td><td>2.19</td></tr>
<tr><td>N Mesa St Lt/S Mesa St Rt to East Riverside Rd</td><td>3</td><td>0.685</td></tr>
</table>

Route	County	Name of Route		Roadway Class	Miles
		Riverside Rd			
84	SM	Old La Honda Rd to Portola Rd	From Old La Honda Rd to the intersection at CONN 84 TO/FR 35-LT	8	2.669
			From CONN 84 TO/FR 35-LT to Portola Rd	3	3.419
145	MAD	9th St Rt to Road 29 south	9th St Rt to Yosemite Ave	3	0.35
			Yosemite Ave to Fig Ave South	5	1
			Fig Ave South to Ave 15 1/2	3	0.45
			Ave 15 1/2 to Road 29 South	8	1.47

2.4.2 Step 2. Identify the variables used in time cost estimation for bicycle performance evaluation

We identified four sets of variables, including variables for the calculation of LTS segments, LTS intersections approaches, LTS crossings, BLOS segments, and BLOS intersections. The time cost for each variable which was included in TASAS bike pilot data collection was used directly. The challenge for this step was that there are some variables used for performance calculation not included in the pilot data collection. For these variables, we used surrogate variables which we expect to have similar data collection procedure to estimate the time cost. For example, the speed limit was used in the performance calculation for LTS segments, but it was not collected in the TASAS pilot data collection. So we chose to use the time cost for collecting bike related signage as the surrogate for the time cost for observing speed limit. The rationale is that, to collect the information about speed limit, the data collector needs to navigate in the street view along the highway segment, which is the same procedure as how we observed the signage along the same highway segment. Another issue that should be noted is that some variables are available in the existing TASAS database and need to be extracted and matched to the segments. For these variables, the time cost is the time it takes to match the intersections and highway segments with the records in TASAS intersection and highway segment database. The variables and surrogates used are shown in Table 5.

Table 5. Variables and surrogates used for the time cost estimation

Bicycle performance measurements	TASAS Bike pilot data collection variables	TASAS variables
LTS variables		
presence of bike lane	Bikeway Type	
presence of parking lane	Vehicle Parking Presence	
street width (through lanes per direction)		thy_lt_lanes_amt & thy_rt_lanes_amt
speed limit or prevailing speed	Signage[a]	
bike lane blockage (rare/frequent)	Access point[a]	
bike lane width (includes marked buffer and paved gutter)	Bikeway Width	
LTS intersection approaches		
presence of pocket bicycle lane	Vehicle left turn pocket[a]	
Width of Street		thy_lt_o_shd_trt_width_amt, thy_lt_trav_way_width_amt, thy_lt_i_shd_trt_width_amt, thy_rt_o_shd_trt_width_amt, thy_rt_trav_way_width_amt, thy_rt_i_shd_trt_width_amt
length of right turn lane	Bikeway width[a]	
LTS crossing variables		
presence of signal		inx_control_code
presence of median		thy_median_type_code
BLOS Links		
Width of outside through lane	Width of the outside through lane	
Width of paving between outside lane stripe and the edge of pavement		thy_lt_o_shd_trt_width_amt, thy_rt_o_shd_trt_width_amt

Bicycle performance measurements	TASAS Bike pilot data collection variables	TASAS variables
Proportion of occupied on-street parking	No. of Parking Spots	
Total number of directional through lanes		thy_lt_lanes_amt, thy_rt_lanes_amt
Midsegment demand flow rate (vph)	Traffic study[b]	
Motorized vehicle running speed (mph)	Traffic study[b]	
Percent heavy vehicles in the midsegment demand flow rate	Traffic study[b]	
Pavement condition rating	Traffic study[b]	
Presence of curb	Vehicle Parking Presence[a]	
Width of bicycle lane	Bikeway width	
BLOS Intersections (signalized intersections only)		
Crossing distance, the width of the side street (including auxiliary lanes and median)	Bikeway width[a]	
Signal control type		inx_control_code
Curb-to-curb width of cross street	Bikeway width[a]	
Left-turn demand flow rate	Traffic study[b]	
Through demand flow rate	Traffic study[b]	
Right-turn demand flow rate	Traffic study[b]	
BLOS segments		
Number of access point approaches on the right side in the subject direction of travel	Access point[a]	

[a] Surrogates for the variables that are not collected in the TASAS Bike pilot data collection.
[b] Variables can only be collected as part of a more comprehensive traffic study and not included under this study.

2.4.3 Step 3. Summarize the total time cost for each route segments identified in the classification

The total time cost includes time for mapping the nodes and approaches, time for setting up the two core tables (node table and approach table) in the data collection table, and time for collecting all the data for that route segment. It should be noted that, here we call it route segment instead of route because we need to split four of the routes into several segments according to their roadway classification as mentioned in the first step. In this way, the time estimation for each roadway type can be applied in the later steps.

2.4.4 Step 4. Reclassify the TASAS highway segment records using CA HSIS roadway classification definition

The TASAS highway segment file was used to obtain the mileage of each roadway class. There is no field for the roadway classification defined by CA HSIS in the TASAS database, so the highway segments in TASAS were re-classified based on the definition of the HSIS roadway classification, using the fields for population type, number of lanes on left and right side of the road, highway group, and access control to determine urban or rural, total number of lanes, divided or not, freeway or non-freeway, respectively. The population area type "urbanized" was counted as "urban" for the classification. The re-classification for TASAS highway segment records are shown in Table 6.

2.4.5 Step 5. Summarize the mileage for each class of the roadway for the entire State Highway System

The length of the highway segments in TASAS was used to obtain the mileage for each class. The mileage results are shown in Table 6.

Table 6. Re-classification of TASAS highway segments using CA HSIS roadway classification

Roadway Classes		Mileage	TASAS Population Group	Access Code	Total # of lanes	Highway Group
1	Urban Freeways	2354.59	Urban + Urbanized	Freewa y	>=4 lanes	Left, Right, Divided, and Undivided
2	Urban Freeways < 4 Lanes		Urban + Urbanized	Freewa y	<4 lanes	Left, Right, Divided, and Undivided
3	Urban Two Lane Roads	60.12	Urban + Urbanized	Non-freeway	2 lanes	Left, Right, Divided, and Undivided
4	Urban Multilane Divided Non-Freeways		Urban + Urbanized	Non-freeway	> 2 lanes	Divided
5	Urban Multilane Undivided Non-Freeways	577.15	Urban + Urbanized	Non-freeway	> 2 lanes	Undivided
6	Rural Freeways		Rural	Freewa y	>=4 lanes	Left, Right, Divided, and Undivided

Roadway Classes			Mileage	TASAS Population Group	Access Code	Total # of lanes	Highway Group
7	Rural Freeways < 4 Lanes		708.12	Rural	Freeway	<4 lanes	Left, Right, Divided, and Undivided
8	Rural Two Lane Roads			Rural	Non-freeway	2 lanes	Left, Right, Divided, and Undivided
9	Rural Multilane Divided Non-Freeways		114.60	Rural	Non-freeway	> 2 lanes	Divided
10	Rural Multilane Undivided Non-Freeways		277.40	Rural	Non-freeway	> 2 lanes	Undivided
99	Others	Rural one lane roads	0.52	Rural	Non-freeway	1 lane	Left, Right, Divided, and Undivided
		Urban one lane roads	0.20	Urban	Non-freeway	1 lane	Left, Right, Divided, and Undivided
		Multilane L or R highway alignment	16.96	Urban and Rural	Non-freeway	>2 lanes	Left and Right
Total			**15,425**				

2.4.6 Step 6. Calculate the total time cost estimate for variables that don't require a traffic study

Once we obtained the time cost for each class of the roadway, we multiplied the time cost by mileage of that class of roadway in TASAS. Then we summed up all the time cost for each class to get the total time cost estimate for the entire state highway system. The pilot routes don't cover all the roadway classes, for example, we only had class 3, 4, 5, and 8. For the other classes, we made some assumptions to obtain their time cost using the classes we have. The details about the assumptions are shown in the next two sections.

2.4.7 Step 7. Split the roadway classes into subgroups according to the width of the treated shoulder

Treated (or paved) shoulder wider than 4 feet is considered as an adequate space for biking along the state highways. To approximate the difference in effort for facilities that have potential bicycle facilities, we further split the roadway classes by treated shoulder width as width on both sides < 4 feet and the other. We then calculated the mileage for each subgroup. The results are shown in Table 5. We estimated the time cost for different subgroups based on the proportion of the mileage for each subgroup.

2.4.8 Step 8. Summarize the time cost for each performance measure

The total time cost for each performance measure shown in Table 7 and Table 8 consists of five parts: (i) mapping time; (ii) node and approach table preparation time; (iii) computer set up time; (iv) data collection time; (v) and TASAS matching time. As described under Data Collection Challenges, the BLOS measure includes variables that require traffic studies and the evaluation of the time required for such studies was outside the scope of this project. As a result, these are not included in the time cost estimates for this work and are not reflected in the results in Table 7 and Table 8. Consequently, the total time costs are a significant underestimation of the actual time cost.

1. Mapping time: The time to draw the nodes and approaches on the customized Google Maps, and to label the ID number for each element. The time for mapping depends on roadway classes. So we have the time cost listed according to the roadway classes in Table 7 and Table 8.
2. Node and approach table preparation time: After the nodes and approaches are mapped, the IDs and the features for the nodes and approaches need to be input into the core tables in the database. All the other data will be connected to the core tables. The time for preparing core tables depends on roadway classes. So we have the time cost listed according to the roadway classes in Table 7 and Table 8.
3. Computer set up time: Every time before the collector input the first data into the database, it takes about one minute to open the route map, open the Google Maps, navigate to the first intersection, and zoom in until the resolution is enough to observe the first variable. We assume that one person will continue collecting the data collection for four hours in the morning and in the afternoon, adding up to eight working hours per day. So the total time cost for setting up the computer to finish the entire state highway system will be the total hours for data collection divided by the data collection time, the time to directly observe the data in the Google Maps and input the measurements into the database.
4. TASAS matching time: In order to use the existing data in TASAS to calculate the performance measures, we need to link the data collected to the records in TASAS database. For example, the nodes should be linked to TASAS intersections, and the approaches should be linked to TASAS highway segments. The time for matching the nodes and approaches to the intersections and roadway segments in TASAS costs 129 hours in total for the entire state highway system. The details about this estimation are shown in Appendix B.

Table 7. Time cost for BLOS measurements for variables that don't require a traffic study

Roadway Classes	Mileage	Shoulder width	Time cost for BLOS (hr)								
			Mileage	Mapping	Node and Approach Table	Links	Intersections	# of Access Point	TASAS Matching	Computer Set Up	Segments [a]
1-Urban Freeways	2354.59	Both side < 4 ft	78.34	8.37	7.37	0.37	0.28	1.33	0.66	(1837.53 + 1610.64 + 215.84 + 120.58 + 375.35 + 129.00) × 1 / 4 / 60	1837.53 + 1610.64 + 215.84 + 120.58 + 375.35 + 129.00 + 17.87
		Other	2276.25	243.22	214.00	10.75	8.04	38.64	19.04		
2-Urban Freeways < 4 Lanes	60.12	Both side < 4 ft	14.03	1.50	1.32	0.07	0.05	0.24	0.12		
		Other	46.10	4.91	4.32	0.22	0.16	0.78	0.38		
3-Urban Two Lane Roads	577.15	Both side < 4 ft	236.21	74.07	64.23	14.78	4.13	24.85	1.97		
		Other	340.93	106.91	92.71	21.33	5.96	35.87	2.85		
4-Urban Multilane Divided Non-Freeways	708.12	Both side < 4 ft	87.01	17.31	15.85	12.33	6.41	8.04	0.73		
		Other	621.10	123.58	113.13	88.03	45.75	57.40	5.19		
5-Urban Multilane Undivided Non-Freeways	114.60	Both side < 4 ft	29.58	19.38	11.99	2.98	0.68	3.81	0.25		
		Other	85.02	55.70	34.47	8.57	1.95	10.96	0.71		
6-Rural Freeways	1885.43	Both side < 4 ft	11.25	1.20	1.06	0.05	0.04	0.19	0.09		
		Other	1874.18	200.18	176.13	8.85	6.62	31.80	15.67		
7-Rural Freeways < 4 Lanes	187.38	Both side < 4 ft	3.48	0.37	0.33	0.02	0.01	0.06	0.03		
		Other	183.91	19.61	17.25	0.87	0.65	3.11	1.53		
8-Rural Two Lane Roads	8461.50	Both side < 4 ft	5483.25	585.76	515.39	25.89	19.37	93.06	45.85		
		Other	2978.25	318.16	279.94	14.06	10.52	50.54	24.90		
9-Rural Multilane Divided Non-Freeways	781.91	Both side < 4 ft	29.99	0.98	1.27	0.20	0.34	0.37	0.25		
		Other	751.92	24.49	31.87	5.01	8.55	9.19	6.29		
10-Rural Multilane Undivided Non-Freeways	277.40	Both side < 4 ft	53.67	5.73	5.04	0.25	0.19	0.91	0.45		
		Other	223.73	23.87	21.00	1.05	0.79	3.79	1.87		
99-Others-Rural one lane roads	0.52	Both side < 4 ft	0.24	0.05	0.04	0.00	0.00	0.01	0.00		
		Other	0.28	0.06	0.05	0.00	0.00	0.01	0.00		
	0.20	Both side < 4 ft	0.00	0.00	0.00	0.00	0.00	0.00	0.00		

Roadway Classes	Mileage	Shoulder width	Mileage	Time cost for BLOS (hr) Mapping	Node and Approach Table	Links	Intersections	# of Access Point	TASAS Matching	Computer Set Up	Segments [a]
99-Others-Urban one lane roads		Other	0.20	0.31	0.27	0.06	0.02	0.11	0.01		
99-Others-Multilane L or R highway alignment	16.96	Both side < 4 ft	4.05	0.43	0.38	0.02	0.01	0.07	0.03		
		Other	12.91	1.38	1.22	0.06	0.05	0.22	0.11		
Total	**15,425**			**1,837**	**1,610**	**215** [b]	**120** [b]	**375**	**129**	**17**	**4,306**[b]

[a] The time cost for BLOS segments consists of the time cost for mapping, preparing node and approach tables, computer set up, matching TASAS, and collecting data for links, intersections, and approaches on the right side in the subject direction of travel.

[b] This time cost is an underestimate because it does not include the time required for a traffic study to collect required variables.

Table 8. Time cost for LTS measurements

Roadway Classes	Mileage	Shoulder width	Mileage	Time cost for LTS (hr) Mapping	Node and Approach Table	Intersection Approaches	Crossings	Variables	TASAS Matching	Computer Set Up	LTS[a]
1-Urban Freeways	2354.59	Both side < 4 ft	78.34	8.37	7.37	0.24	0.66	2.00	0.66	(1837.53 + 1610.64 + 94.85 + 129.00 + 625.98 + 129.00) × 1 / 60	1837.53 + 1610.64 + 94.85 + 129.00 + 625.98 + 129.00 + 18.45
		Other	2276.25	243.22	214.00	7.10	19.04	58.19	19.04		
2-Urban Freeways < 4 Lanes	60.12	Both side < 4 ft	14.03	1.50	1.32	0.04	0.12	0.36	0.12		
		Other	46.10	4.91	4.32	0.14	0.38	1.18	0.38		
3-Urban Two Lane Roads	577.15	Both side < 4 ft	236.21	74.07	64.23	3.85	1.97	40.95	1.97		
		Other	340.93	106.91	92.71	5.56	2.85	59.10	2.85		
4-Urban Multilane Divided Non-Freeways	708.12	Both side < 4 ft	87.01	17.31	15.85	4.42	0.73	17.59	0.73		
		Other	621.10	123.58	113.13	31.53	5.19	125.58	5.19		
5-Urban Multilane Undivided Non-Freeways	114.60	Both side < 4 ft	29.58	19.38	11.99	0.65	0.25	6.89	0.25		
		Other	85.02	55.70	34.47	1.87	0.71	19.80	0.71		
6-Rural Freeways	1885.43	Both side < 4 ft	11.25	1.20	1.06	0.04	0.09	0.29	0.09		
		Other	1874.18	200.18	176.13	5.85	15.67	47.89	15.67		

Roadway Classes	Mileage	Shoulder width	Mileage	Time cost for LTS (hr) Mapping	Node and Approach Table	Intersection Approaches	Crossings	Variables	TASAS Matching	Computer Set Up	LTS[a]
7-Rural Freeways < 4 Lanes	187.38	Both side < 4 ft	3.48	0.37	0.33	0.01	0.03	0.09	0.03		
		Other	183.91	19.61	17.25	0.57	1.53	4.69	1.53		
8-Rural Two Lane Roads	8461.50	Both side < 4 ft	5483.25	585.76	515.39	17.10	45.85	140.13	45.85		
		Other	2978.25	318.16	279.94	9.29	24.90	76.11	24.90		
9-Rural Multilane Divided Non-Freeways	781.91	Both side < 4 ft	29.99	0.98	1.27	0.22	0.25	0.67	0.25		
		Other	751.92	24.49	31.87	5.42	6.29	16.74	6.29		
10-Rural Multilane Undivided Non-Freeways	277.40	Both side < 4 ft	53.67	5.73	5.04	0.17	0.45	1.37	0.45		
		Other	223.73	23.87	21.00	0.70	1.87	5.71	1.87		
99-Others-Rural one lane roads	0.52	Both side < 4 ft	0.24	0.05	0.04	0.00	0.00	0.01	0.00		
		Other	0.28	0.06	0.05	0.00	0.00	0.01	0.00		
99-Others-Urban one lane roads	0.20	Both side < 4 ft	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
		Other	0.20	0.31	0.27	0.02	0.01	0.17	0.01		
99-Others-Multilane L or R highway alignment	16.96	Both side < 4 ft	4.05	0.43	0.38	0.01	0.03	0.10	0.03		
		Other	12.91	1.38	1.22	0.04	0.11	0.33	0.11		
Total	**15,425**			**1,837**	**1,610**	**94**	**129**	**625**	**129**	**18**	**4,445**

[a] The time cost for LTS consists of the time cost for mapping, preparing node and approach tables, computer set up, matching TASAS, and collecting data for intersection approaches, crossings, and other variables.

2.4.9 Time Costs Estimates Results for BLOS and LTS

Based on the methodology described in this chapter we provided the following estimates for applying BLOS and LTS performance measure across the SHS. Our time cost estimate for the BLOS for the data elements that do not require a traffic study is 4,306 hours. Additional resources would be needed to conduct traffic studies to provide the motorized traffic flow and running speed as required by BLOS. Our time cost estimates for the applying the BLOS performance measure across the SHS is 4,445 hours. These estimates reflect the time needed for the actual data collection process which includes the time for mapping, preparing node and approach tables, computer set up, matching TASAS, and collecting data. However, these time cost estimates do not include the time needed for training data collection personnel, and management effort.

3 Pilot California-specific Performance Measure

The data collection challenges and methodological weaknesses of existing performance measures make creation of a custom performance measure for the state a worthwhile effort. In this chapter, we describe a pilot study to test a new methodology for developing bicycle performance measures. The approach is inspired by the strengths and weaknesses of existing measures. It is important that performance measures be developed empirically, creating a quantitative link between objective measures of the roadway environment and subjective measures of bicyclist user experience. While the BLOS models have been developed empirically, they are based on surveys conducted 20 years ago in a state, Florida, with a different roadway environment and different traffic culture than California (Landis et al. 1997, Dowling et al. 2008, HCM 2010). Additionally, the results average the ratings of users encompassing a spectrum of skill, comfort, and experience levels. LTS, using a rating system based on the Portland four types of cyclists, provides a score that accounts for the heterogeneity of cyclists and translates more meaningful than a score of A through F.

In this pilot study, we conducted a user experience survey soliciting response to roadway infrastructure and environment shown in bicycle video simulations on 38 local and state road segments in the San Francisco Bay Area. In combination with demographic and bicycling experience data about the respondents, we developed a pilot model to classify bicyclists according to their characteristics and road attribute preferences and then estimate the choice each class would make on particular road segment. We then propose options for using the model to develop a bicycle performance measure that accounts for difference in bicyclist preferences.

3.1 Data Collection

Three types of data collection were required as input for the pilot California-specific segment performance measure. The first, roadway infrastructure attributes, was performed as part of the TASAS for bikes study. The second type, video recordings of cycling on the study roads, served as input for the last piece, a survey to collect user response to the cycling experience on roads with different features. This data collection is described below.

3.1.1 Video Data Collection

We used bicycle video simulations to capture the bicyclist user experience of riding on a road. Jensen (2007) described several advantages to video simulations over field survey responses: respondents can rate a high number of segments in a short period of time, respondent group can be more diverse, more cost effective than having the respondents on site, and no traffic risk for the respondents.

We recorded video simulation data using a GoPro Hero 4 video camera center-mounted on a bicycle handlebar, following extensive trial and error to determine the best approach to capture an immersive bicycling experience.

It was a challenge to minimize vibration while simultaneously maintaining a consistent angle and stable view of the road ahead. Mounting the camera to the cyclist's body minimized transfer of vibration from poor road surface to the camera, but it presented other challenges. Mounting the camera to the helmet made it difficult to maintain a consistent forward view of the road, as well as a reliable angle of view; any movement of the head would also move the camera. Mounting the camera to the chest or shoulder could eliminate the problems with heading turning, but the camera could capture the arms and handlebars in the view and possibly bias the responses to the survey. We hypothesized that less experienced rides may be intimidated by seeing drop handlebars, or that women may have trouble imagining themselves on the road if the arms in the video belong to a man.

We determined that the handlebar was the best location to mount the camera to maintain a consistent forward viewpoint and to avoid capturing any parts of the rider. This camera location created two problems: the viewpoint is not at eye-level and a very light camera like the GoPro cannot dampen road vibration. Attempts to raise the camera using mounting extensions severely amplified the vibration. These test videos could not be watched for more than a few minutes before some viewers became nauseous. A Gimbal steadicam device for the GoPro proved to be ineffective at reducing vibration and possibly defective. Reducing the vibration was more important than camera height, so we shot the final videos with the camera mounted just above the handlebar. To minimize vibration, we only used clips where the road surface was smooth, and we performed post-processing in Adobe After Effects to reduce any remaining vibration and crop out undesired content (e.g. brake hoods on drop handlebars).

All videos for the pilot study were shot in District 4, on a mixture of state and local roads to capture greater variability of attributes (Table). The videos can be viewed at http://bit.ly/BLOS-videos.

Table 9. Roads included in video data collection

Road Name	Cross Streets or Landmarks	Hwy No.	Community
19th Ave	Holloway to Denslowe	1	San Francisco
19th Ave	Winston to Rossmoor	1	San Francisco
19th Ave	Eucalyptus to Winston	1	San Francisco
35th Ave	Victor to Wisconsin	n/a	Oakland
4th St	Addison to University	n/a	Berkeley
4th St	Virginia to Delaware	n/a	Berkeley
Alcatraz Ave	Colby to Hillegass	n/a	Oakland
Ashby Ave	California to King	13	Berkeley
Ashby Ave	Deakin to Telegraph	13	Berkeley
Ashby Ave	Colby to Regent	13	Berkeley
Ashby Ave	Hillegass to Benvenue	13	Berkeley

Road Name	Cross Streets or Landmarks	Hwy No.	Community
Ashby Ave	Elmwood to Piedmont	13	Berkeley
Broadway	Golden Gate Way to Lake Temescal	n/a	Oakland
Cabrillo Hwy	South towards Martini Creek	1	Uninc. San Mateo
Cabrillo Hwy	South towards Martini Creek	1	Uninc. San Mateo
California St	Francisco to Delaware	n/a	Berkeley
Camino Pablo	South of El Toyonal	n/a	Orinda
Chabot Rd	College to Presley	n/a	Oakland
Channing Way	Dana to Ellsworth	n/a	Berkeley
Grizzly Peak Blvd	Latham to Forest	n/a	Berkeley
Grizzly Peak Blvd	South of Claremont	n/a	Oakland
Miles Ave	College to Forest	n/a	Oakland
San Pablo Ave	Harrison to Darthmouth	123	Berkeley/Albany
San Pablo Ave	Gilman to Harrison	123	Berkeley
San Pablo Ave	Cedar to Virginia	123	Berkeley
San Pablo Ave	Parker to Carleton	123	Berkeley
San Pablo Dam Rd	Wildcat to Old San Pablo Dam	n/a	Uninc. Contra Costa County
San Pablo Dam Rd	South of Fire trail No 3	n/a	Uninc. Contra Costa County
Skyline Blvd	Fort Funston to Olympic	35	San Francisco
Skyline Blvd	Snake to Manzanita	n/a	Oakland
Sloat Blvd	Crestlake to Gabilan	35	San Francisco
Tunnel Rd	Oak Ridge to Uplands	13	Berkeley
Tunnel Rd	Hiller to Vicente	13	Berkeley
Tunnel Rd	Vicente to Bridge	13	Oakland
Virginia St	Chestnut to West St Path	n/a	Berkeley
Wildcat Canyon Rd	South (East) of Central Park Dr	n/a	Uninc. Alameda County
Wildcat Canyon Rd	North (East) of South Park	n/a	Uninc. Contra Costa County
Wildcat Canyon Rd	East of Central Park Dr	n/a	Uninc. Contra Costa County

Table 10. Video data collection categories

Facility Type	Parking lane	Volume	Number of Videos
Shared Lane	Yes	High	11
Shared Lane	Yes	Low	6

Facility Type	Parking lane	Volume	Number of Videos
Shared Lane	No	High	1
Shared Lane	No	Low	7
Bicycle Lane or Shoulder	Yes	High	none
Bicycle Lane or Shoulder	Yes	Low	5
Bicycle Lane or Shoulder	No	High	1
Bicycle Lane or Shoulder	No	Low	6
Protected Bicycle Lane	No		1

3.1.2 Survey Development

The survey contained two main sections, cycling experience questions followed by responses to the videos. The first section included a number of questions from previous surveys along with new ones, with a goal of capturing users' level of cycling experience and cycling habits to categorize respondents by their style of bicycling. The video section included six response questions following each of 8 randomly selected videos. The video questions were designed to capture four important elements of human factors, safety, comfort, service, and performance. The final question addressed the likelihood of the respondent riding on the road shown in the video, and the response was to be used as the dependent variable in the choice model. See Appendix C for the complete list of survey questions.

Each participant was shown eight videos during the survey. To make sure that a variety of road types were shown, the videos were categorized by three variables, presence of bicycle facility, presence of curbside parking, and low or high automobile volume. Each category contained at least one video, except for the category with a bicycle lane or shoulder, parking lane, and high traffic volume. This category was replaced with a video showing a protected bicycle lane. One random video from each of the eight categories was shown to each participant. Three categories contained only one video, while the remaining categories contained at least five. The order of categories was randomized for each video to avoid order effects.

Both versions of the survey asked the same questions for eight randomly selected videos, but the in person experiment asked two additional questions following each human factors question ("why?" and "what would improve it?") with the objective of giving space to provide more detail. The in-person interview was designed to serve comparison purposes with the online version and gain qualitative rather than quantitative insights, hypothesizing that people in the interview would be more concentrated or thoughtful when filling the survey. Given the small sample size for the in person experiment, we didn't include these answers in the model. We only considered the qualitative responses provided by participants to validate the survey methodology and inform some of our recommendations.

3.1.3 Survey implementation

Email invitations describing both survey options (online and in person) were sent on Friday, April 8, 2016, to several student lists as well as SafeTREC's news alert list. Emails were sent directly by the owners of the lists, who forwarded the message on to list members. The participants who volunteered for the in-person interview were redirected to a page where they could select days and times that fit for them, email or phone number, and preferred contact method (email, call or text).

The online survey was closed on April 17, 2016, and the in-person interviews were conducted between April 13 and 27, 2016.

The online survey was completed by 221 participants. People who completed this version of the survey were entered in a drawing to receive one of five $10 Amazon gift cards. The second option was to complete the survey in-person at SafeTREC offices. A $10 Amazon gift card was provided as an incentive for all participants who completed the in-person experiment, totaling 14 people.

For the in person surveys the participants were chosen on a first come first served basis. A meeting room in SafeTREC was set up to receive them, where the videos were projected on a 7-foot-wide screen with the sound from the computer. The videos could be repeated as many times as the respondents desired.

The convenience sample of respondents was not representative of the general population, so the results cannot be generalized. Members of the distribution lists the survey was sent to are likely to have a personal interest in transportation.

3.2 Summary of survey results

3.2.1 Online survey

The online survey received 221 completed responses. Ages were fairly evenly distributed between 21 and 60 (Figure 2). The age group with the most responses was 21 to 30, which was expected due to the student email lists used to distribute the survey link. Approximately 60 percent of respondents were male and 40 percent female (Figure 3). For trip purpose, commuting and recreation were the most common responses (Figure 4). Up to 94 percent of the respondents own a bike.

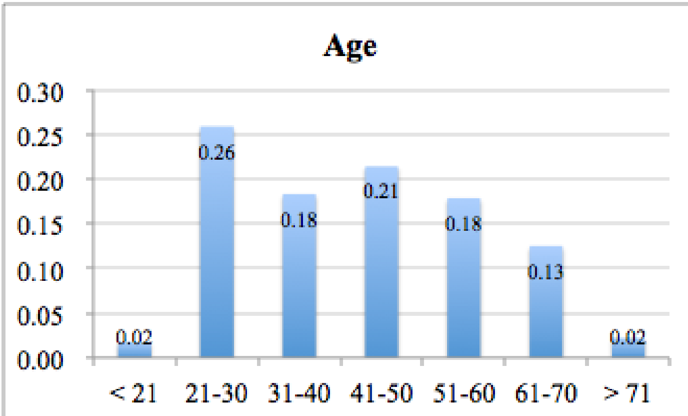

Figure 2. Age distribution of online survey respondents

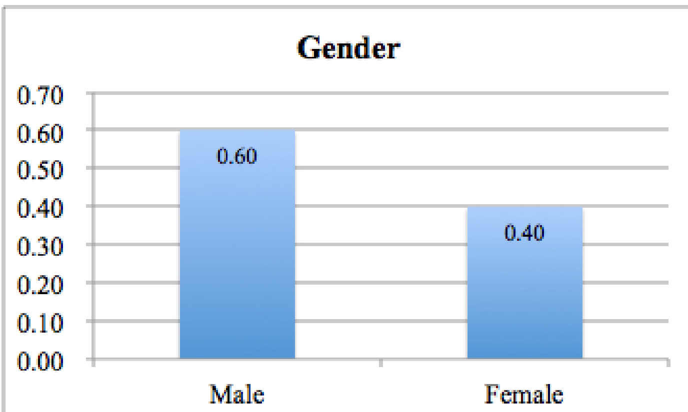

Figure 3. Gender distribution of online survey respondents

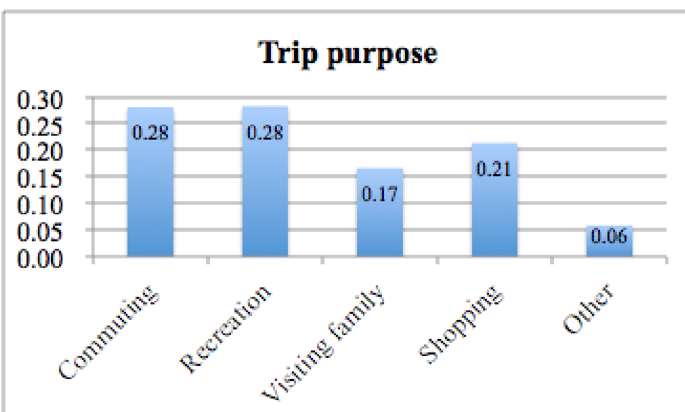

Figure 4. Typical bicycle trip purposes of online survey respondents

3.2.2 In-person survey

Qualitative analysis of in-person survey transcripts (with qualitative responses) followed a systematic, hybrid thematic analysis designed to support the identification, analysis and reporting of themes (as described by Braun and Clarke 2006). Data transcripts were fully transcribed and analyzed on a sentence-by-sentence basis (using Excel software). Key themes and patterns within the data were then identified. Analysis was conducted iteratively, with data driven codes developed and emergent overarching themes identified in line with the objectives of the study (Braun and Clarke 2006, Bryman 2004). Reliability was enhanced through the systematic review by two independent researchers, assessing for face validity and consistent coding.

We identified 10 broad themes from the data in the responses to the 896 open-ended user experience questions (14 respondents × 8 videos × 8 questions) (Figure 5). These themes were comprised of 76 individual codes referring to specific features, conditions, or feelings that influenced the participants' ratings of each bicycle video simulation. Some order effects were observed, as 395 codes were identified for the safety questions, which came first, and only 180 codes were identified for the service questions, which came last.

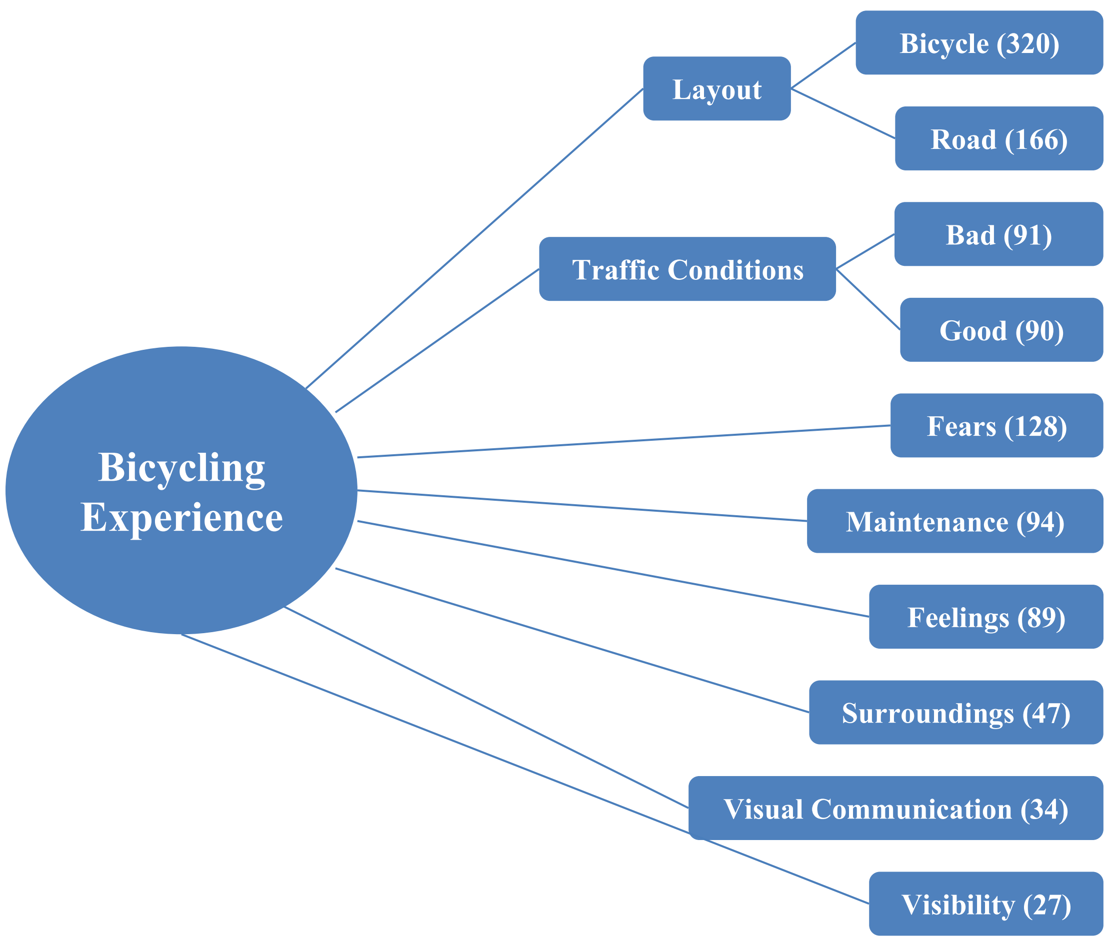

Figure 5. Themes (number of references) of responses to bicycle simulation videos

Bicycle layout, the layout or presence of bicycle facilities or bicycle space, was by far the most common theme in comments, with 320 references. There were more than 170 references to presence, quality, or absence of bicycle lanes. Eleven of 14 respondents made multiple references to wanting more bicycle lanes or improvement of the existing lanes. A video rating of "*safe*" was explained by one respondent by its "*Clear separation, marked bike lane. Bike lane is also pretty wide*" (participant number 14 (P14) female aged 31-40 years). A small minority of respondents disliked bicycle lanes and suggested improvements such as "*Eliminate bike lane. Share in line, not side by side*" (P12, male aged 51-60 years). Most respondents wanted more space for bicyclists, as well as a buffer, physical barrier, or some other kind of protection from cars.

One hundred sixty-six references to other specifics of road layout made up the second most common theme. Inadequacy or adequacy of width of lanes, bicycle lanes, or road shoulders dominated this theme. Safety could be improved by, for example, a "*wider road, bike lane*" (P13, female aged 31-40 years) or "*wider shoulder or alternative bike/jogging hiking path"* (P10, male aged 51-60 years).

Respondents were particularly sensitive to traffic conditions, which were referenced 181 times. Bad conditions included too much traffic, traffic that was too fast, cars coming too close, or high speed differential. One participant's explanation for a video rated as "*unsafe*" was "*traffic speed is higher relative to cyclist, cars are not keeping in lane"* (P10, male aged 51-60 years). This theme was most often mentioned in relation to safety, but also represented a similar percentage of code instances for comfort and enjoyment. Good traffic conditions included light, no, or slow traffic, as well as absence of parked cars. One respondent rated a segment as "safe" because of *"Low traffic speed despite a narrow roadway and no dedicated cycling facilities"* (P10, male aged 51-60 years).

Many respondents identified specific conditions or situations that would cause them discomfort or fear. This theme appeared in 128 comments. Many disliked riding near parked cars and feared the door zone or dooring (*"Parked cars can open doors into bike lane"* (P3, female aged 41-50 years)). We found many expressions of fear of collisions and an unexpected negative response to curves. One particular quiet road popular with local recreational cyclists (Figure 6), the video of which included no other traffic, received poor ratings from both respondents who viewed it. One respondent explained her "very unsafe" rating, "*No bike lane, one lane of traffic, blind curve. Trees in the way"* (P2, female aged 51-60 years). The other respondent, explaining her rating of "poorly" on the service question, wrote "*I could be pushed off the road or run over"* (P6, female aged 61-70 years) Comments in this theme expressed a certain fatalism about being hit by a car—"*Fast traffic, no areas to bail out to avoid an accident"* (P11, male aged 21-30 years). Some preferred to stay off the road altogether—*"I would ride in the sidewalk"* (P12, male aged 51-60 years).

Figure 6. Screen capture from the video of a two-lane road near a regional park in Berkeley, CA

Respondents made 94 comments referencing the maintenance status of the roads, including the road surface quality, presence of obstructions or debris, or obtrusive vegetation. Possibly due to the pragmatic leaning of utilitarian bicyclists, most references to plants or trees were negative, seeing the foliage as a physical or visual obstruction. One respondent commented, *"Safe but perhaps too narrow because there are trees sticking out and no sidewalk as a temporary alternative"* (P4, male aged 21-30 years)

Feelings, particularly safety and comfort, were mentioned 89 times, mostly in the explanations for the service ratings. *"Safety would make me not opt for this even though the street looks pleasant"* (P5, female aged 21-30 years). Surroundings were a dominant theme of the enjoyment explanations. *"Although it is very scenic, being hit/falling would make it unenjoyable"* (P5, female aged 21-30 years).

Codes related to visual communication, which included references to pavement markings and signage, were mostly mentioned as methods to improve roads. They appeared in 34 comments. According to one respondent, safety could be improved by *"a bike symbol to increase awareness of drivers"* (P11, male aged 21-30 years). Another responded stated, *"People usually drive safer when there is a bike symbol"* (P3, female aged 41-50 years).

Visibility, referenced 27 times, was one of the minor themes, with respondents expressing concern about their own visibility, visibility of threats, lighting on the road, or the conditions riding at night. One respondent recommended improving comfort with *"more space on the shoulder, maybe mirrors at the turns to improve visibility around the corners"* (P11, male aged 21-30 years).

3.3 Pilot Model

Over the past 25 years, many traffic engineers and researchers have presented different typologies and classifications, which provided a better understanding of the distinctive behaviors among cyclists, and offered guidance to traffic designers working on bikeways and bicycle plans targeting different types of cyclists. For example, in 2006, Geller (HCM 2010) suggested that Portland's bicycling community comprised four types of cyclists, and gave an estimate of the percentage of each type based on professional experience, logical assumptions, and Census data. This section builds on the evidence that there are different classes of cyclists, and provides a proof of concept for a methodology to analytically separate different classes of cyclists.

A 1994 the Federal Highway Administration report grouped bicycle riders into "advanced bicyclists," "basic bicyclists," and "children," which was based mainly on their skills and experience, and which failed to analyze the percentage of each class (Wilkinson et al. 1994). Winters et al. (2011) classified cyclists as "potential cyclists," "occasional cyclists," "frequent cyclists," and "regular cyclists" by their bicycling frequency, and each percentage was concluded from a survey conducted in metropolitan Vancouver. The Portland typology mentioned above classified cyclists into "strong and fearless," "enthused and confident," "interested but concerned," and "no way no how" (Geller 2009). These four types were determined by cyclists' level of comfort while riding on different roadway conditions. Dill and McNeil (2013) designed a survey to validate Geller's percentage estimates in Portland typology and the similar value showed the Portland typology's usefulness to distinguish different types of cyclists.

All of the typologies mentioned above share some similarities. First, the classification standard usually depends on one or two cyclists' characteristics, such as bicycling frequency, comfort level, etc. Studies have shown that some other important socio-demographic characteristics can also have an impact on bicycle use, including age (Rietveld and Daniel 2004, Sener et al. 2009), income (Pucher and Beuhler 2008), gender (Pucher and Beuhler 2008, Krizek et al. 2005), ethnic origin (Moudon et al. 2005, Pucher and Beuhler 2008), car ownership and use (Dill and Voros 2007, Pucher et al. 2010), and bicycle ownership (Pinjari et al. 2008, Rietveld 2000). Although neither the characteristics examined nor their results are entirely consistent across studies, it is still reasonable to examine whether the combined information of these personal attributes gives us more insight into how to classify cyclists.

Second, behavioral analysis usually follows the classification of cyclists. For example, Geller came to the conclusion that "interested but concerned" cyclists do not like speeding cars rather than saying cyclists who do not like speeding cars should be classified as "interested but concerned." In fact, implications of classification methods from cyclist's behavior would be useful. Thus, this methodology seeks to find a way of combining the classification and behavioral analysis processes.

Third, these typologies usually assign a cyclist to a single class. However, in reality, the assignment process is likely to be probabilistic, meaning that each classified cyclist may have a chance of also belonging to other classes, notwithstanding a very low probability.

We propose a Latent Class Choice Model (LCCM) to achieve: (1) including several characteristics of cyclists for classification; (2) integrating behavioral analysis into the classification process; and (3) treating the classification as probabilistic.

3.3.1 Methodology

LCCM, in essence, is a choice model. In the present study, the "choice" is how a cyclist rates a single roadway segment, for example, positively or negatively. Thus, the meaning of "choice" is different from selecting a better roadway segment from several alternatives. Derived from Walker and Li (Walker and Li 2007), a general introduction of LCCM in the background of cyclists "rating" behavior will be provided.

A class membership model and several class-specific choice models together construct a LCCM. In general, the class membership model provides information as to how likely it is that a cyclist belongs to each class, whereas the class-specific choice models provide information on how each class behaves.

For the class membership model, the probabilities that a cyclist belongs to each latent class based on his/her social demographics (e.g., gender), preferences (e.g., cycling frequency), and responses to bicycling-related questions (e.g., "Do you feel comfortable with riding at night?"). These questions will be explained in more detail in the Data section. It is reasonable to assume that these responses contribute to helping identify a cyclist's inherent bicycling style and which class he or she is more or less likely to belong to. In the class membership model, the probability that cyclist n with characteristics Z_n belongs to latent class s is denoted as:

$$P(s|Z_n)$$

The class-specific choice models represent the rating behavior of each class and vary across latent classes. They predict the probability that a cyclist positively rates a given roadway segment conditional on a latent class. This class-specific choice probability is written as:

$$P(i = 1|X_n, s)$$

where i denotes the choice set $\{0,1\}$, Z_n denotes the attributes of the alternative and s denotes the class. The class-specific choice model may vary across classes on several dimensions, such as setting different parameter weights, applying different alternatives in the choice set, utilizing different model structure or different decision rules. Since the emphasis is on interpreting the difference of rating behavior between each class in a consistent way, the same specifications are used in class-specific choice models.

Obviously, the probability of a cyclist belonging to each latent class is unknown, hence neither of the above two equations can be estimated individually. Thus, it is necessary to connect them and to estimate these two components simultaneously. For cyclist n, the probability of choosing a given roadway segment is equal to the sum over all latent classes of the probability in the class-specific membership model conditional on class ($P(i = 1|X_n, s)$) multiplied by the probability of belonging to that class ($P(s|Z_n)$), denoted as:

$$P(i = 1|Z_n) = \sum_{S} P(i = 1|X_n, s)P(s|Z_n)$$

To be more specific, if it is assumed there are two latent classes: aggressive cyclists and cautious cyclists, then the probability that cyclist *n* is aggressive is expressed as $P(Aggresive|Z_n)$ and the probability that cyclist *n* is cautious is expressed as $P(Cautious|Z_n) = 1 - P(Aggresive|Z_n)$. The class membership model can take on a number of forms, such as binary logit for this example. There is then a class-specific choice model for these two latent classes modeling the probability of choosing a given bicycle infrastructure conditional on being in that class: $P(i = 1|X_n , Aggresive)$ and $P(i = 1|X_n , Cautious)$, where X_n can include the attributes of the roadway segment (bikeway type, speed limit etc.). The class-specific choice behavior would vary across the two classes; for example, an aggressive cyclist may place more weight on speed limit and volume, whereas a cautious cyclist may pay more attention to bikeway type (Standard, buffered or shared use). Then the probability of a cyclist positively rating a particular roadway segment is:

$$P(i = 1|X_n, Z_n) = P(i = 1|X_n, Aggressive) \times P(Aggressive|Z_n)$$

$$+P(i = 1|X_n, Cautious) \times P(Cautious|Z_n)$$

The advantage of such a latent class choice model framework is that it enables simultaneous estimation of the parameters of the class membership model and the class-specific choice, and the number of classes can be resolved endogenously. In addition, the model is established on the existing observations without using another variable to indicate which type of cyclist the individual is. Furthermore, it can capture underlying, unobservable discrete segmentation (class) beyond the hypothesis since it is “latent.”

The primary modeling issues of a latent class choice model are identifying the number of classes, the form of the class membership model, the class-specific choice models, and the model specifications. The number of classes is determined by the number of parameters estimated, the final log-likelihood, the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), and also the interpretation of the model results. The class-membership models are logit equations, as are the class-specific choice models. These issues will be further discussed in the model framework section.

3.3.2 Model Framework

Figure 7 shows the proposed model framework. Class membership is hypothesized to be a function of observable characteristics of cyclists. The disturbances denote unobserved factors that also play a role in class membership model. Let U_{ns} be the utility of latent class s for individual n, which may be expressed as follows:

$$U_{ns} = \alpha_s + Z_n'\gamma_s + \varepsilon_{ns},$$

where α_s is alternative specific constant of class s; Z_n is a vector of characteristics of cyclist n; γ_s is a vector of parameters associated with the cyclist's characteristics; and ε_{ns} is a random variable assumed to be i.i.d. Extreme Value across cyclists and classes with mean zero and variance $\pi^2/6$.

Assuming all cyclists are utility maximizing, the class membership model can be stated as multinomial logit model. The probability that cyclist n belongs to class s is written as:

$$P(q_{ns} = 1) = \frac{\exp(\alpha_s + Z_n'\gamma_s)}{\sum_{s'=1}^{S} \exp(\alpha_{s'} + Z_n'\gamma_{s'})},$$

where q_{ns} equals one if cyclist n belongs to latent class s, and zero otherwise.

Next the focus shifts to class-specific choice model. As mentioned before, each cyclist is randomly assigned to rate eight different videos respectively. The alternative set for each video can be seen as binary (choosing the given bicycle infrastructure or not choosing), thus the probability that cyclist n over video v chooses alternative j conditional on this cyclist belonging to latent class s is written as:

$$P\left(y_{nvj} = 1 | q_{ns} = 1\right),$$

where y_{nvj} equals one if cyclist n chooses alternative j over video v and zero otherwise.

The class-specific choice model is specified as logit, Let $U_{nvj|s}$ be the utility of alternative j over video v for cyclist n given that the cyclist belongs to latent class s, which may be expressed as follows:

$$U_{nvj|s} = \alpha_{j|s} + X_{nvj}'\beta_{j|s} + \varepsilon_{nvj|s},$$

where X_{nvj}' is a vector of attributes of alternative j over video v for cyclist n; $\beta_{j|s}$ is a vector of parameters associated with these attributes; $\varepsilon_{nj|s}$ is a random variable assumed to be i.i.d. Extreme Value across cyclists, videos and classes with mean zero and variance $\pi^2/6$. Assuming again that all cyclists are utility maximizers, the class specific choice model may be represented as follows:

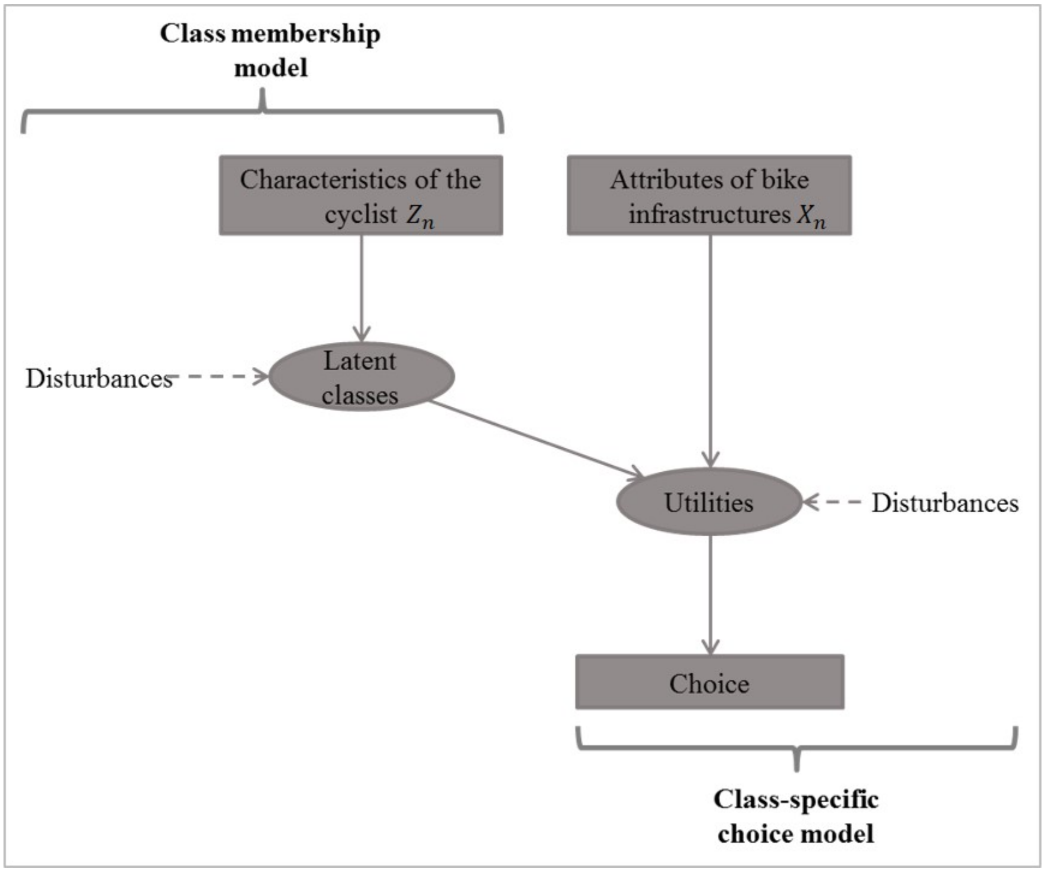

Figure 7. LCCM framework

$$P\left(y_{nvj} = 1 | q_{ns} = 1\right) = \frac{\exp(\alpha_{j|s} + X'_{nvj}\beta_{j|s})}{\sum_{j' \in J_{nv|s}} \exp\left(\alpha_{j'|s} + X'_{nvj'}\beta_{j'|s}\right)},$$

where $J_{nv|s}$ is the choice-set for video for cyclist n, given that the cyclist belongs to latent class s. The above equation can be combined iteratively over videos to yield the likelihood conditional on class s for the eight responses of a given cyclist. Such a probability may be expressed as follows:

$$P(y_n | q_{ns} = 1) = \prod_{v=1}^{V} \prod_{j \in J_{nv|s}} \left[\frac{\exp(\alpha_{j|s} + X'_{nvj}\beta_{j|s})}{\sum_{j' \in J_{nv|s}} \exp\left(\alpha_{j'|s} + X'_{nvj'}\beta_{j'|s}\right)}\right]^{y_{nvj}},$$

where V denotes the number of videos shown to cyclist n. V might not always be equal to eight due to the existence of incomplete surveys. Then combining the class membership model, we may yield the joint likelihood function for each cyclist n, shown as:

$$P(y_n) = \sum_{s=1}^{S} P(q_{ns} = 1) \times P(y_n | q_{ns} = 1),$$

where S denotes the number of classes, which is determined during the process of estimating models with different number of classes. And three classes model is selected as the most appropriate model using a combination of goodness-of-fit measures, including higher BIC, AIC and more reasonable behavioral interpretation of each model.

The likelihood function for the sample population can be expressed as follows:

$$L(\boldsymbol{\beta}, \boldsymbol{\gamma}; \boldsymbol{y}, \boldsymbol{X}, \boldsymbol{Z}) = \prod_{n=1}^{N} \sum_{s=1}^{S} P(q_{ns} = 1) \times P(y_n | q_{ns} = 1),$$

where N denotes the total number of cyclists participating the experiment. The above equation should be maximized to determine the estimates for the parameters β and γ. These models are estimated in Python using the Expectation-Maximization (EM) Algorithm (Dempster et al. 1977).

3.3.3 Estimation Results

The estimation results for the model specification and number of classes are presented in Table 11. It includes parameter estimates for three class-specific choice models and the class membership model. The final model is the outcome of a combination of statistics (t-stat, AIC, BIC, etc.) and reasonable interpretation, and some variables are thus removed from the model during this process.

Since for each class-specific model, the variance of the error term is standardized to $\pi^2/6$ respectively (i.e. the scale parameter is different from each model), the magnitude of the coefficients among three models cannot be directly compared. Another column "Scaled Est" (Estimate value divided by the absolute value of "Standard bikeway dummy" in each model) is provided to help interpret the behavior, which represents the relative magnitude of each attribute. The following part of this section will discuss the implied behavioral features of each class, based on which class labels are assigned to each type of cyclist.

Table 11. Estimation Results

Class-specific Choice Models				
Class 1:Cautious				
Parameter	Est	SE	t-stat	Scaled Est
Constant	-0.50	0.60	-0.84	
Standard bikeway dummy	1.98	0.35	5.63	1.00
Buffered bikeway dummy	3.07	0.27	11.53	1.55
Bicycle boulevard dummy	2.59	0.47	5.52	1.31
Speed limit	-0.51	0.17	-3.08	-0.26
High volume traffic	-0.23	0.28	-0.80	-0.11
Parking density	-0.73	1.63	-0.45	-0.37
Class 2:Enthusiastic				
Parameter	Est	SE	t-stat	Scaled Est
Constant	-0.37	0.40	-0.93	
Standard bikeway dummy	1.30	0.30	4.32	1.00
Buffered bikeway dummy	2.25	0.27	8.23	1.73
Bicycle boulevard dummy	2.63	0.70	3.78	2.03
Speed limit	0.24	0.12	2.03	0.19
High volume traffic	-0.51	0.19	-2.70	-0.39
Parking density	-2.40	0.98	-2.45	-1.85
Class 3:Recreational				
Parameter	Est	SE	t-stat	Scaled Est
Constant	1.13	1.43	0.79	
Standard bikeway dummy	-2.30	1.38	-1.67	-1.00
Buffered bikeway dummy	-1.18	0.71	-1.66	-0.52
Bicycle boulevard dummy	-1.71	1.29	-1.33	-0.74
Speed limit	-0.15	0.43	-0.35	-0.07
High volume traffic	-1.15	0.61	-1.89	-0.50
Parking density	-0.82	3.78	-0.22	-0.36
Class Membership Model				
Parameter	Est	SE	t-stat	
Class-specific constant (Enthusiastic)	0.46	0.44	1.06	
Class-specific constant (Recreational)	-2.08	1.20	-1.74	
"Separation from cars" is important (Enthusiastic)	-0.83	0.37	-2.22	
"Separation from cars" is important (Recreational)	-0.86	0.96	-0.90	
"Slow traffic" is important (Enthusiastic)	-1.36	0.39	-3.50	
"Slow traffic" is important (Recreational)	-1.72	0.90	-1.91	
"Bicycle facility" is important (Enthusiastic)	-0.35	0.38	-0.91	
"Bicycle facility" is important (Recreational)	-0.41	0.97	-0.42	
Comfortable with "Riding at night" (Enthusiastic)	0.70	0.39	1.78	
Comfortable with "Riding at night" (Recreational)	1.41	1.36	1.04	
High biking frequency (Enthusiastic)	1.28	0.43	2.94	
High biking frequency (Recreational)	1.92	0.92	2.09	
Male (Enthusiastic)	0.50	0.39	1.27	
Male (Recreational)	-0.28	1.33	-0.21	

3.3.4 Class Specific Analysis

The three cyclist classifications that were identified in the analysis are as follows:

Cautious cyclists (Class 1): Comprising forty-three percent of the sample population, cautious cyclists have a clear preference for better facilitated bicycle infrastructures and have negative attitudes toward higher speed limits, higher volumes, and higher parking density. The results of the class membership model also give backing to their behavior. Compared with enthusiastic and recreational cyclists, they convey a strong inclination toward "separation from cars" and bicycling environment with "slow traffic." In addition, cautious cyclists are not accustomed to riding at night and have a relatively lower bicycling frequency than the other two classes, all of which are consistent with their choice behavior.

Enthusiastic cyclists (Class 2): At fifty percent of the sample population, this class behaves similarly to the cautious cyclists except for their sensitivity to speed limits. They also hope to be protected and better served (concluding from the positive signs of variables denoting bikeway types), however, this class is less averse to riding with faster motorized traffic (positive coefficient of speed limit). The class membership model also verifies that this class of cyclists is more experienced and confident than cautious cyclists considering that they count "slow traffic" as less essential and feel more relaxed with riding at night.

Recreational cyclists (Class 3): This class comprises seven percent of the sample population and reacts negatively to attributes of bicycle infrastructure, suggesting they prefer to ride in mixed traffic, but they also have the strongest dislike of high traffic volumes. They have the highest bicycling frequency among all cyclists, which indicates that the class might comprise those who are very experienced and would still bicycle regardless of the bicycling environment. This class is identified as recreational cyclists based on their behavior.

Another interesting finding is that, in the class membership model, gender does not play a significant role in classification of different population segments. The same phenomenon is also observed in the two-class model and four-class model which were evaluated, which implies that gender might not play a role in classifying cyclists.

To provide a more intuitive sense of the preference difference among the three classes, the estimated parameters are entered into three class-specific choice models and the top 3 favorable videos are selected for each class. A representative screenshot image for each video is presented in Figure 8. The images indicate that two videos overlap for cautious and enthusiastic cyclists, which confirms the conclusion that these two classes behave similarly. The most favorable videos for recreational cyclists are completely different from those of the other two classes and were taken on roads that are popular among local recreational cyclists for scenic rides.

Figure 8. Favorable videos for each class

3.3.5 LCCM for a performance measure

The LCCM demonstrates great potential for creating an improved bicycle performance measure by revealing what types of cyclists prefer different roads. For instance, the roads preferred by recreational cyclists tend to be two-lane roads with rural surroundings, while these same roads are disfavored by the cautious and enthusiastic cyclists, who favor urban roads with bicycle facilities and may use the bicycle primarily for utilitarian purposes. The SHS contains more than 8,000 miles of 2-lane urban roads, many of which may be acceptable or near-acceptable to the recreational cyclists who would tend to ride outside urban areas. A performance measure that is based on an average of all rides, may rate a road unfavorably because it is not accounting for the type of cyclist who would ride on it. Additionally, the accommodations to improve performance on a rural road for a recreational cyclist may be different from what would be done for a utilitarian cyclist. These differences need to be accounted for.

LCCM results can be used in a number of different ways to meet the particular needs of a project. The output of the class-specific choice model is the probability that a given class will choose to ride on a facility. For a hypothetical set of latent classes, *A*, *B*, and *C*, we could have:

$$P_{classA}(ride) = 0.3$$

$P_{classB}(ride) = 0.8$

$P_{classC}(ride) = 0.5$

One approach to present these results would be to assign an acceptable threshold at which class members would be willing to ride on the facility. If the threshold were 0.5, we would say that classes B and C would ride on the facility. For more nuanced results, we can set multiple thresholds, like:

poor < 0.5

good < 0.8

excellent ≥ 0.8

In this case, the score for class A would be "poor," for class B "excellent," and class C "good." For internal use, the probabilities may be most helpful and the presentation can depend on the audience.

An important characteristic of these results is that they are not ordinal. While LTS uses an ordinal typology, the LCCM approach can account for different preferences that could be associated with skill, experience, or ride purpose. Table 7 demonstrates how the probability of riding changes for the 3 classes in the pilot model when bicycle facilities are added to the road show in Figure 9. A standard bicycle lane improves conditions for "cautious" and "enthusiastic" riders, but is detrimental for "recreational" riders. The result is similar when a buffered lane is added, but all probabilities are higher than for a standard facility.

Table 7. Change in probability when a bicycle facility is added

Facility	$P_{cautious}(ride)$	$P_{enthusiastic}(ride)$	$P_{recreational}(ride)$
Original facility in Figure 9	0.14	0.56	0.68
Adding a standard bicycle lane	0.55	0.82	0.18
Adding a buffered bicycle lane	0.78	0.92	0.40

Figure 9. Screen capture from video on a road segment preferred by "recreational" riders

There is a clear value to expanding the pilot study to conduct a state-wide experiment with a LCCM which will establish a user-class based performance measure for the California SHS.

4 Evaluation of Performance Measures

In this chapter, we describe the approach taken and the results of the evaluation of BLOS and LTS as they compare to each other and the responses of the survey participants. We applied the performance measures to the 38 road segments that were video recorded for the survey. Then we compared the BLOS and LTS scores directly to the survey ratings for the matching road segments. This allowed us to examine the ability of the performance measures to capture user experience of a variety of infrastructure configurations and roadway environments.

4.1 Applying BLOS

We applied the segment BLOS measure to the 38 roadway segments from the survey, using the methodology described in the 2010 HCM (HCM 2010). The data requirements were accommodated as follows:

- The infrastructure widths were taken using the measurement tools in Google Earth and Google Maps.
- Proportion of on-street parking occupied was estimated based on the length of the segment recorded in the video, the number of the parked cars along the segment in the video, and an average parking space length of 20 feet (6 meters).
- Pavement condition was judged based on the table provided in the HCM for that purpose. It was not possible within time and budget constraints to conduct a traffic study to estimate the mid-segment demand flow rate, the percent heavy vehicles, or the motorized vehicle running speed. These variables were estimated based on the data available within the videos of each segment.
- We approximated speed using the known speed limit and an estimate of whether cars in the video were travelling faster or slower than the limit.
- Vehicle flow was based on the number of motorized vehicles passing the bicycle video camera in the same direct during the video recording. This value is an underestimate of actual flow, but may provide a better spontaneous measure for comparison to the video ratings. Percent heavy vehicles was set at zero for all segments, since the videos recorded no heavy vehicle traffic.
- The BLOS values were calculated with the equations provided in the 2010 HCM, and the final scores were determined based on the thresholds provided. We used segment BLOS, which combines the scores for link and intersection BLOS. The intersection BLOS, however, only applies to signalized intersections, which were not present at either end of the roads segments in the study.

4.2 Applying LTS

Data collection for the LTS segment measure required fewer assumptions and approximations. Widths were taken using the same measurement tools, and speed limit was collected over Google

Street View. Bike lane blockage was determined based on our personal experience with the road segments. For each road segment, we used the appropriate tables from (Mekuria et al. 2012).

4.3 Comparison

The road segments in the study captured the full range of LTS scores and B through F for BLOS scores. Both measures were more weighted toward the negative, giving scores in the poor end of the range for 22 of the road segments. Table shows the Pearson's correlation coefficients for the performance measures and the survey responses to the corresponding road segments. The survey rating is the response to a question about the likelihood of the respondent riding on the road segment, where 1 is very likely and 5 is very unlikely. Both performance measures were positively correlated with survey rating, LTS (ρ=0.60) much more strongly than BLOS (ρ=0.29). They had a very weak correlation with each other (ρ=0.10).

Both BLOS and LTS were most strongly correlated with the enjoyment score among the survey responses. This result was unexpected, especially given that the survey used for the BLOS model asked about safety and comfort (Landis et al. 1997). Enjoyment is also a less practical question for planning purposes. All of the different ratings from the survey were, however, very strongly correlated (ρ>0.9).

Table 12. Pearson's correlation coefficients for performance measure scores and survey ratings

	BLOS Score	LTS Score	Survey Rating	Safety	Comfort	Enjoyment	Service
BLOS Score	1						
LTS Score	0.10	1					
Survey Rating	0.29	0.60	1				
Safety	0.22	0.58	0.97	1			
Comfort	0.27	0.59	0.97	0.98	1		
Enjoyment	0.44	0.64	0.94	0.91	0.92	1	
Service	0.23	0.56	0.97	0.98	0.97	0.91	1

The BLOS scores only had a weak correlation with the survey ratings, which is confirmed in the scatter plot in

Figure 10. Ten road segments received a D and this score encompassed the largest range of survey rating values. It included the best rated road segment from the survey, a one-lane, one-way local street with a buffered bicycle lane, and the worst rated road segment, a six-lane divided state highway running through an urban area.

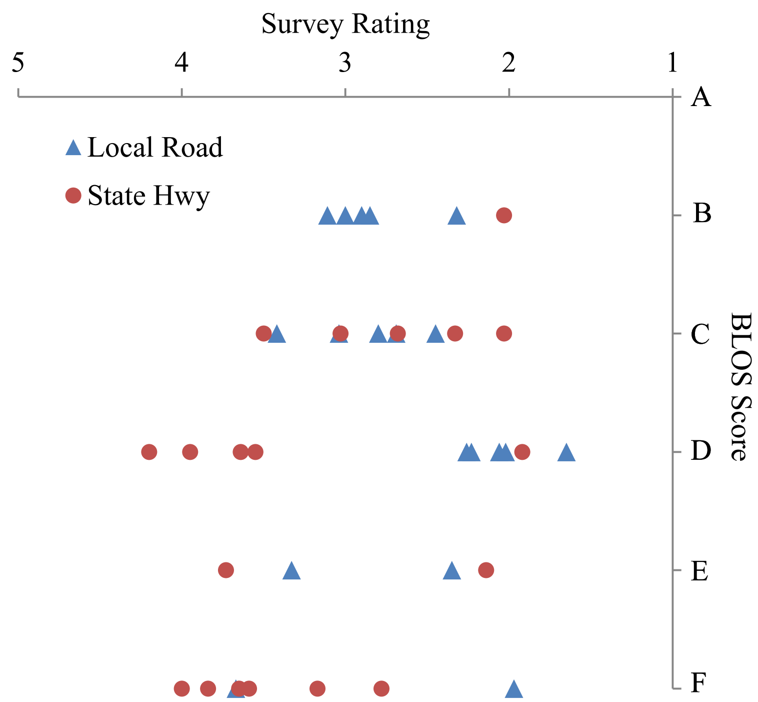

Figure 10. Scatter plot of survey ratings and BLOS scores

The four top rated roads from the survey scored three Ds and an F. The top rated segment from the survey, on Miles Ave. in Oakland (Figure 11), is a quiet one-way street with a bicycle lane buffered on either side, from both vehicular traffic and parked cars. It received a BLOS score of D and an LTS score of 1. The second top rated segment from the survey, on Tunnel Rd. (Rte. 13) in Oakland (Figure 11), has high traffic volumes, but a wide protected bicycle lane provides separation for bicyclists. It scored a D in BLOS and 1 in LTS. BLOS is unable to capture the benefits of a physical barrier or other separation, and as the qualitative analysis indicated, these are the features that many bicyclists desire.

Figure 11. Miles Ave. in Oakland received the best survey rating

Figure 12. Tunnel Rd. from Hiller to Vicente received the second best survey rating

LTS scores were most numerous at the extremes, either 1 or 4 (Figure 13). Fourteen roadway segments received a score of 4, spanning nearly the full range of survey ratings. That range includes segments on a 6-lane, divided urban state highway with on-street parking and traffic travelling significantly over the speed limit as well as a two-lane, undivided arterial along a regional park with a large bicycle lane. All of the road segments given an LTS score of 4 were rated as such due to high traffic speeds. While the degree of unpleasantness may not have come through clearly to the survey respondents, there is some nuance that LTS fails to capture, especially when a bicycle facility is present.

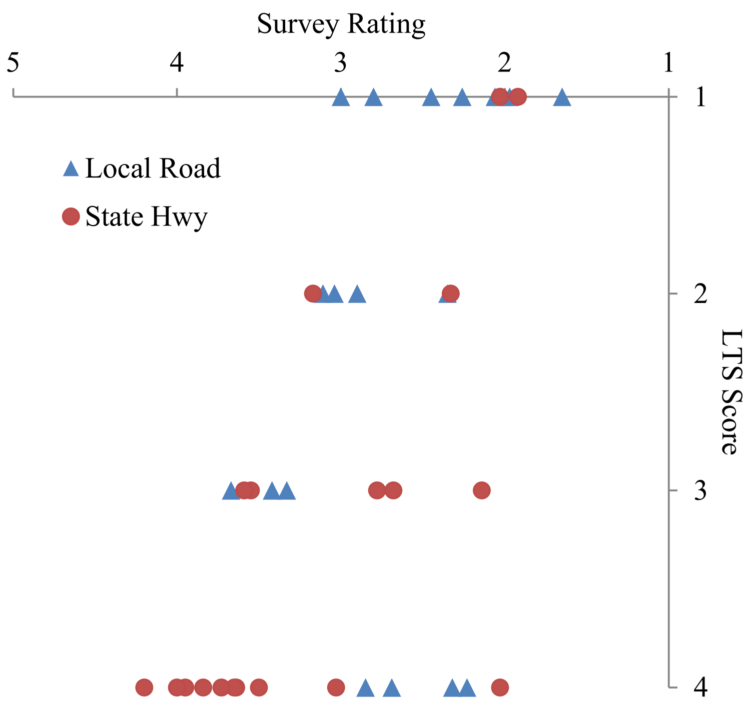

Figure 13. **Scatter plot of survey ratings and LTS scores**

Comparing the BLOS and LTS scores directly, we can get a better picture of the differences between the measures. Figure 14 is a bubble plot, with the size of the bubble representing the frequency of each combination of scores. The largest bubbles are at the two extremes for LTS and D, a middle score, for BLOS, suggesting little agreement between the measures. The two measures did agree in giving the worst scores to three segments along the same four-lane urban arterial on the state highway system. The most extreme disagreement, with a BLOS of F and LTS of 1, was a two-lane bicycle boulevard in a residential neighborhood. The survey rating was closely aligned with the LTS score.

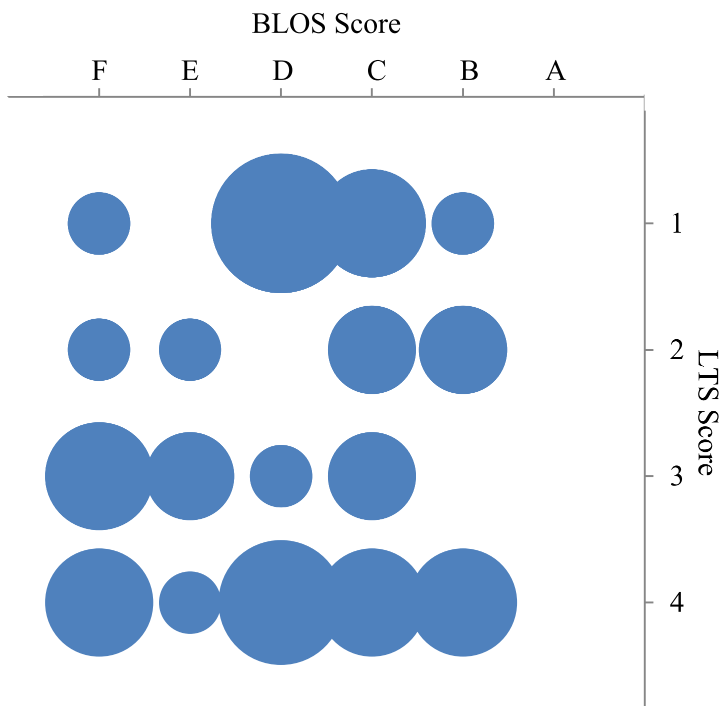

Figure 14. **Bubble plot of BLOS and LTS scores**

The disagreement between the two performance measures highlights the different factors that are weighted heavily. The segment BLOS equation contains a high constant (greater than the maximum threshold for a score of A), and the only variable that can reduce the score is greater width of outside through lane. All other variables, even if they have low values, will make the BLOS score worse. For instance, the best pavement condition rating will still increase the equation result, as will the complete absence of vehicle traffic. The number of driveways is also weighted heavily and does not account for whether the driveways are for business parking lots or single family residences, which present very different risk of conflict. LTS, on the other hand, does not account for vehicle volumes or pavement condition. The score is heavily influenced by the speed of traffic, which is the factor that explains all the cases where LTS had a worse score than BLOS.

5 Conclusion

This report describes a study to identify the most feasible and practicable bicycle performance measure for application to the California SHS. We selected BLOS and LTS for evaluation, as common measures that are recommended as national standards or widely in use, respectively. We developed time cost estimates for the application of these measures, 4,300 hours for BLOS and 4,400 hours for LTS, but the BLOS estimates represent the time required assuming the availability of motorized traffic flow and running speed from a traffic study, which was outside the scope of this study and may require additional data collection efforts and analysis.

Comparison of BLOS, LTS, and user survey ratings of 38 road segments highlighted the inability of existing performance to capture impact of newer bicycle facility designs, such as protected bicycle lanes with physical barriers. BLOS was weakly correlated with the survey ratings ($\rho=0.29$), while LTS had a moderate correlation ($\rho=0.60$).

Problems with BLOS have been identified and acknowledged elsewhere (Petritsh, Landis, and Scorsone 2014, Huff and Liggett 2014). Other versions of BLOS, based on similar datasets, including Landis et al. (1997) and NCHRP (2008), may be less problematic and produce scores more aligned with actual bicyclist user experience. These measures, however, incorporate a very similar list of variables, including vehicle traffic data that will require expensive field traffic studies at a large scale for application statewide.

A pilot latent class choice model demonstrated the feasibility of applying this methodology to bicyclist performance measures. We used bicyclist experience, preference, and roadway ratings from a survey to classify cyclists into three groups, cautious cyclists, enthusiastic cyclists, and recreational cyclists. These groups each showed different preferences for facilities and conditions that can help to guide roadway improvements towards the types of cyclists who will use them. LCCM models used for this purpose provide rich results on user preferences and can be represented in both complex and simple ways, depending on the audience they are meant for.

Due to the limited validity of using existing performance measures for the California state highway system, we recommend further development of a California-specific performance measure based on the LCCM methodology.

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7 Appendix A: TASAS variables and values

Table 8. TASAS variables potential relevant to bicycling and their values

Variable Name	Description	Values
thy_lt_lanes_amt / thy_rt_lanes_amt	Number of lanes, left/right side	One Lane Two Lanes Three Lanes 4 to 6 Lanes 7 to 8 Lanes > 8 Lanes
thy_lt_spec_features_code / thy_rt_spec_features_code	Road bed features, left/right side	'A' - One Lane Road With Turnouts For Passing 'B' - Lane Transitions 'C' - Passing or Truck Climbing Lane 'D' - Bus Lane 'E' - Auxiliary Lane (Included in No. Lanes Field) 'F' - Auxiliary Lanes (Included in No. Lanes Field) 'G' - Tunnel 'H' - Toll Plaza and Approaches 'J' - "Bug" Or Border Patrol Station 'K' - Bottom Deck of Two-Deck Structure 'L' - Top Deck of Two-Deck Structure 'M' - Construction Zone Open To Traffic 'N' - Median Lane Is HOV Lane 'P' - Median Lanes Are HOV Lanes 'Q' - Reversible Peak-Hour Lane(s) 'Z' - No Special Feature
thy_lt_o_shd_trt_width_amt / thy_rt_o_shd_trt_width_amt	Left/right outside shoulder treated width (ft)	0 - Zero 1-3 - 1-3 Ft 4-6 - 4-6 Ft 7-9 - 7-9 Ft 10-13 - 10-13 Ft 14-99 - 14-99 Ft
thy_median_type_code	Median type	Undivided, Not Separated or Striped

		Undivided, Striped
		Undivided, Reversible Peak Hour Lane(S)
		Divided, Reversible Peak Hour Lane(S)
		Divided, Two-Way Left Turn Lane
		Divided, Continuous Left-Turn Lane
		Divided, Paved Median
		Divided, Unpaved Median
		Divided, Separate Grades
		Divided, Separate Grades With Retaining Wall
		Divided, Sawtooth (Unpaved)
		Divided, Sawtooth (Paved)
		Divided, Ditch
		Divided, Separate Structure
		Divided, Railroad or Rapid Transit
		Divided, Bus Lanes
		Divided, Paved Area, Occasional Traffic Lane
		Divided, Railroad and Bus Lane
		Divided, Contains Reversible Peak-Hour Lane(S)
		Divided, Other
thy_highway_access_code	Access control	Conventional - No Access Control
		Expressway - Partial Access Control
		Freeway - Full Access Control
		One-Way City Street - No Access Control
thy_terrain_code	Terrain code	Mountainous
		Rolling
		Flat
thy_design_speed_amt	Design speed	< 30 MPH
		30 MPH
		35 MPH
		40 MPH
		45 MPH
		50 MPH
		55 MPH
		60 MPH
		65 MPH

		> 70 MPH
thy_adt_amt	AADT amount	0
		1-100
		101-500
		501-1,000
		1,001-2,000
		2,001-5,000
		5,001-10,000
		10,001-15,000
		15,001-20,000
		20,001-40,000
		>= 40,001
inx_main_lanes_amt	# of lanes on main street	One Lane
		Two Lanes
		Three Lanes
		4 to 6 Lanes
		7 to 8 Lanes
		> 8 Lanes
inx_cross_lanes_amt	# of lanes on crossing street	One Lane
		Two Lanes
		Three Lanes
		4 to 6 Lanes
		7 to 8 Lanes
		> 8 Lanes
inx_mainline_adt	Mainline AADT	0
		1-100
		101-500
		501-1,000
		1,001-2,000
		2,001-5,000
		5,001-10,000
		10,001-15,000
		15,001-20,000
		20,001-40,000
		>= 40,001
inx_xstreet_adt	Cross-street AADT	0
		1-100
		101-500
		501-1,000
		1,001-2,000
		2,001-5,000
		5,001-10,000
		10,001-15,000
		15,001-20,000
		20,001-40,000

		>= 40,001
inx_control_code	Traffic control type	No Control Stp Sgn X/Stret Stp Sgn Mainlne 4 Way Stop Sgns 4 Way Flsh Red-X 4 Way Flsh Red-M 4 Way Flsh Red-A Yield Sgn X-Strt Yield Sgn Mnline Sgnl Pretime -2p Sgnl Pretime -Mp Sgnl Semi-Act 2p Sgnl Semi-Act Mp Sgnl Full-Act 2p Sgnl Full-Act Mp
inx_main_left_channel_code	Mainline left channel code	Curbed Median Left Turn Channelization No Left Turn Channelization Painted Left Turn Channelization Raised Bars Left Turn Channelization
inx_main_right_channel_code	Mainline right channel code	No Right Turn Channelization Channelization Provided For Right Turns
inx_cross_left_channel_code	Cross-street left channel code	Curbed Median Left Turn Channelization No Left Turn Channelization Painted Left Turn Channelization Raised Bars Left Turn Channelization
inx_cross_right_channel_code	Cross-street right channel code	No Right Turn Channelization Channelization Provided For Right Turns

8 Appendix B: Time cost to link to TASAS

8.1 Steps

1. Open the route table and the TASAS intersection table.
2. Filter the TASAS intersection table by the route name and the county name.
3. Check the “N_Name” of the first node in the node table.
4. Search the “N_Name” in “inx_intersection _name” in TASAS intersection table.
5. Find the “inx_connection_id” in TASAS intersection table for that intersection, and copy it into the cell in the route table.
6. Assume we have the postmile value for each node in the route table. We add these values to the approach table for each “From_Node” and “To_Node” pair.
7. Open the TASAS highway segment table.
8. Filter the TASAS highway segment table by the route name and the county name.
9. Check the begin and end postmile value. Find the value the same as the from/end node in the approach table.
10. Copy the segment ID into the approach table.

8.2 Time cost for the test

Route: 013
From node: Ashby & Regent
To node: Ashby & Alvarado
Number of nodes: 17
Number of approaches: 31
Mileage: 1.05 mi
Time to link intersections: 525.60 s = 8.76 min (for 17 intersections)
Time to link approaches: 269.58 s = 4.49 min (for 31 approaches)
Total time cost: 795.18 s = 13 min
Set up time to link intersections: 51.43 s = 0.86 min/task
Set up time to link approaches: 136.32 s = 2.27 min/task

8.3 Time cost for SHS

Number of intersections: 18244
Number of highway segments: 46485 = Number of approaches: 46485*2=92970
Total time cost for SHS: 0.86/17*18244+2.27/31*92970=7730.74 min=128.85 hr

9 Appendix C: Survey

Questions in *italics* were only included in the in person survey.

Informed Consent

You are invited to participate in a UC Berkeley study about the factors that make roads more or less bicycle friendly. This research is being led by Offer Grembek, PhD, Co-Director of the UC Berkeley Safe Transportation Research and Education Center, and Prof. Joan Walker of the Department of Civil and Environmental Engineering at UC Berkeley. Participation in this research is voluntary. If you have any questions or concerns about this study, you may contact Offer Grembek at (510) 642-5553 or grembek@berkeley.edu or Julia Griswold, Postdoctoral Researcher, at (510) 643-1799 or juliagris@berkeley.edu.

I consent to participate in this research.

___________________________________ ___________

Signature Date

General Questions

Please circle your answer(s).

1. What is your age in years?

    a. <21
    b. 21-30
    c. 31-40
    d. 41-50
    e. 51-60
    f. 61-70
    g. >71 years

2. What is your gender?

    a. Female
    b. Male
    c. Other _______________

3. Do you own a bicycle? Yes _____ No _____

4. For how many years have you been riding a bicycle? ______

5. Do you ride in the city? Yes _____ No _____

If yes, what are the typical purposes for your bicycle trips (*circle all that apply*)?

a. Commuting
b. Recreation
c. Visiting family / friends
d. Shopping
e. Other _______________

6. How many days per week do you typically ride a bicycle? ______

7. How many miles per week do you typically ride on urban or suburban streets?

a. < 5
b. 5 – 19
c. 20 – 40
d. > 40

8. Have you had any experiences while riding a bicycle that have kept you from riding more?
Yes _____ No _____

If yes, please explain…

9. On which of the following road types do you typically ride? (*circle all that apply*)

a. Major streets (no bicycle lane)
b. Residential streets (no bicycle lane)
c. Bicycle lane
d. Bicycle paths/trails
e. Sidewalks
f. Other _______________

10. What features are most important when you select your route on bicycle? (*circle all that apply*)

a. Slow traffic
b. Few cars
c. Most direct path
d. Less climbing
e. Designated bicycle facilities
f. Separation from cars
g. Other _______________

11. Would you like to ride a bicycle more than you currently do? Yes _____ No _____

12. Do you wear a helmet when you ride a bicycle?

    a. Always
    b. Usually
    c. Sometimes
    d. Seldom
    e. Never

13. Do you wear high visibility clothing when you ride a bicycle?

    a. Always
    b. Usually
    c. Sometimes
    d. Seldom
    e. Never

14. How comfortable would you feel riding a bicycle at night?

    a. Very comfortable
    b. Comfortable
    c. Neither comfortable nor uncomfortable
    d. Uncomfortable
    e. Very uncomfortable

15. Do you ever choose not to ride your bicycle due to adverse weather conditions?
    Yes _____ No _____

    If yes, under which conditions will you NOT ride? (*check all that apply*)

    a. Threat of rain _____
    b. Drizzle _____
    c. Steady rain _____
    d. Heavy rain _____
    e. Snow/Ice _____
    f. Fog _____
    g. Cold weather _____ (below what temperature ____F)
    h. Hot weather _____ (above what temperature ____F)

Video Questions

In the following section of the survey, we ask you to watch 8 video clips of bicycling on different roads, followed by questions about the experience of riding on each road. For each video clip, imagine that you are riding a bicycle for your most typical trip purpose, and the roadway segment is part of one route option for your trip.

Video 1

1. Overall, how <u>safe</u> would you feel bicycling on this road?

    a. Very safe
    b. Safe
    c. Neither safe nor unsafe
    d. Unsafe
    e. Very unsafe

    Why?

    What would improve it?

2. Overall, how <u>comfortable</u> would you feel bicycling on this road?

    a. Very comfortable
    b. Comfortable
    c. Neither comfortable nor uncomfortable
    d. Uncomfortable
    e. Very uncomfortable

    Why?

    What would improve it?

3. Overall, how <u>enjoyable</u> would bicycling on this road be?

    a. Very enjoyable
    b. Enjoyable
    c. Neither enjoyable nor unenjoyable
    d. Unenjoyable
    e. Very unenjoyable

    Why?

    What would improve it?

4. Overall, how well does this road <u>serve</u> your bicycling needs?

    a. Very well

b. Well
c. Neither well nor poorly
d. Poorly
e. Very poorly

Why?

What would improve it?

5. Can you tell me any factors that might make you choose not to bicycle on this road?

6. How likely would you be to choose a route that includes this road segment if there were reasonable alternatives?

    a. Very likely
    b. Likely
    c. Neither likely nor unlikely
    d. Unlikely
    e. Very unlikely