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16. ABSTRACT

Bicycle level of service (BLOS) measures are essential tools for transportation agencies to monitor and prioritize improvements to infrastructure for bicyclists. They attempt to relate objective measures of the roadway environment to subjective measures of cyclist safety or comfort. Existing BLOS measures were developed in other regions and do not account for the roadway features and driving culture in California. Additionally, as bicycle facility improvements have advanced, existing measures do not account for many of the changes, such as introduction of buffered and protected bicycle lanes. A previous BLOS pilot study utilized and tested a statistical and behavioral modeling approach to developing BLOS measures for the California state highway system (SHS).

An ideal BLOS for the SHS should strike a balance between broad applicability across the state and sufficient detail to capture localized biking preferences. It should be an empirically driven method capable of accommodating bicyclist preferences and heterogeneity, thereby enabling its usability for both level of service and traffic stress assessments. This project proposes a segment-based BLOS measure that effectively achieves these objectives by integrating two innovative methodologies for BLOS development: a Latent Class Choice Model (LCCM) and Virtual Reality (VR) simulation. VR-based videos are incorporated into a stated preference survey, which capture individuals' biking preferences, and which in turn serve as inputs for the modeling process.

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Developing segment and intersection-level BLOS measures for the SHS

FINAL REPORT

Task Order 65A0801

by

Safe Transportation Research and Education Center
University of California, Berkeley

for

California Department of Transportation

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Executive Summary

Bicycle level of service (BLOS) measures are essential tools for transportation agencies to monitor and prioritize improvements to infrastructure for bicyclists. They attempt to relate objective measures of the roadway environment to subjective measures of cyclist safety or comfort. Existing BLOS measures were developed in other regions and do not account for the roadway features and driving culture in California. Additionally, as bicycle facility improvements have advanced, existing measures do not account for many of the changes, such as introduction of buffered and protected bicycle lanes. A previous BLOS pilot study utilized and tested a statistical and behavioral modeling approach to developing BLOS measures for the California state highway system (SHS).

An ideal BLOS for the SHS should strike a balance between broad applicability across the state and sufficient detail to capture localized biking preferences. It should be an empirically driven method capable of accommodating bicyclist preferences and heterogeneity, thereby enabling its usability for both level of service and traffic stress assessments. This project proposes a segment-based BLOS measure that effectively achieves these objectives by integrating two innovative methodologies for BLOS development: a Latent Class Choice Model (LCCM) and Virtual Reality (VR) simulation. VR-based videos are incorporated into a stated preference survey, which capture individuals' biking preferences, and which in turn serve as inputs for the modelling process.

The proposed methodology was developed following a four-step process:

Design of the VR scenarios: Thirty VR scenarios were produced to resemble roads and bike facilities found on the SHS. Each video is unique and showed different bicycle facilities and roads with varying degrees of traffic conditions, surface conditions, and bike infrastructure. The VR videos were created by first identifying key variables that impact individuals' biking preferences. Key variables included were: urban/rural context, traffic volume, vehicle speed, proportion of heavy-duty vehicles, bike lane width, buffer width, barrier height, and pavement quality. Second, an orthogonal design was implemented to systematically combine these variables in a balanced manner. Lastly, the estimated variable combinations were incorporated in the development of the VR videos, creating a diverse set of scenarios for participants to evaluate during the stated preference survey.

Design of the stated preference survey: The survey captured people's stated preferences for bike routes along with self-reported socio-demographic data, bicycling experience and frequency, perceptions on level of skill or comfort on a bike, and preferred facility types. The survey sought to capture responses from a large pool of Californians, including groups that are typically underrepresented in research, and was therefore distributed online, both in English and Spanish, to numerous cycling organizations and one Community Based Organization.

The survey consisted of two sections. In the first section, respondents provided demographic information and details about their biking habits, including age, gender, ethnicity, riding frequency, and infrastructure preferences. The second section included the choice questions where respondents were asked to choose between pairs of VR videos.

Overall, the survey collected some diversity of responses from individuals with varying biking habits and perceptions about biking. The vast majority of respondents were frequent bikers between the ages of 21-40 that like to bike and do so for a variety of purposes, but in particular for recreation. Yet, despite the prevailing trend, the survey did captured input from individuals of all age groups, genders, and different biking habits and preferences. Notably, respondents expressed a range of opinions concerning bike comfort and safety, pointing to some heterogeneity.

Model Estimation: Two LCCM models were estimated. The first one, with three classes, is a constrained version of the second one, with four classes, and both are very closely related. The four-class model unveiled the following typology for California bicyclists:

- *Road Cycling Enthusiasts (7%):* Members of this class are individuals that are 40+ years old that bike a few times a month or less, and typically bike for recreational purposes only. They have a strong inclination towards biking and would bike on any street, regardless of the type of infrastructure available. Road cycling enthusiasts respond positively to bike lanes, strongly dislike buffers of any kind (barriers, median, parking lanes, simple buffer strips), and prefer to bike on multi-lanes streets and avoid streets with high traffic volumes.
- *Occasional Recreational Bicyclists – Moderate Sensitivity to Bike Infrastructure (25%):* Members of this class are 40+ years old, do not bike frequently, and consider bike infrastructure to be more important to them than *Road Cycling Enthusiasts.* Members of this class inherently prefer not to ride a bike. They respond positively to bike facilities like bike lanes, buffers, and barriers for protection, and prefer to ride roads with light traffic, a small percentage of heavy-duty vehicles, and good pavement conditions.
- *Occasional Recreation Bicyclists – High Sensitivity to Bike Infrastructure (27%):* Members of this class are mostly identical to *Moderate Sensitivity to Bike Infrastructure* class members. They differ in that they show a higher sensitivity to bike infrastructure and poor traffic conditions.
- *Indifferent to Bike Infrastructure (39%):* Members of this class are individuals for whom bike infrastructure is not very important when choosing their bike route. These individuals have a weaker, almost neutral, response to most bike infrastructure, especially compared to the other classes.

BLOS development: A BLOS measure was constructed using the utility equations of the four-class LCCM model. The BLOS measure is a set of tables that illustrate how the probability of riding on a road segment with any bike facility versus one that has no bike facilities increases as new features are added and as the dimensions of those features increase.

Introduction

Bicycle level of service (BLOS) measures are essential tools for transportation agencies to monitor and prioritize improvements to infrastructure for bicyclists. They attempt to relate objective measures of the roadway environment to subjective measures of bicyclist safety or comfort. Existing BLOS measures were developed in other regions and do not account for the roadway features and driving culture in California. Furthermore, the methodologies by which they were developed are either empirically estimated from a particular location and cannot be applied to other places, or they are too general and cannot capture nuances in biking preferences for bicyclists in different regions. Additionally, as bicycle facility improvements have advanced, existing measures do not account for many of the changes, such as introduction of buffered and protected bicycle lanes. A previous BLOS pilot study utilized and tested a statistical and behavioral modeling approach to developing BLOS measures for the California state highway system (SHS).

An ideal BLOS methodology for California's SHS should strike a balance between broad applicability across the state and sufficient detail to capture localized biking preferences. It should be an empirically driven method capable of accommodating bicyclist preferences and heterogeneity, thereby enabling its usability for both level of service and traffic stress assessments. This project proposes a segment-based BLOS measure that effectively achieves these objectives. The proposed methodology consists of estimating a latent class choice model (LCCM). These models achieve the dual purpose of identifying the typology of bicyclists in California based on their stated preferences for bike infrastructure, traffic and roadway conditions, and estimating the utility for each class within the typology, delivering valuable insights into the various bicyclist groups and their unique needs. This models will allow districts to assess how well their state roads serve as a connector for or barrier to bicycle activity based upon empirical data and only require the administration of a survey to be constructed.

The output of this project will support the Bicycle Collision Monitoring Program (BCMP) by allowing Caltrans to evaluate the impact of specific improvements on bicycle level of service using empirical data. Furthermore, such models can potentially be used to refine the identification of high collision bicycle corridors that are an important part of BCMP.

The remainder of this report is divided into two primary sections. The first section comprises a comprehensive literature review that critically examines existing BLOS measures and their associated methodologies. The second section delves into the methodology for constructing the LCCM models that serve as the basis for the BLOS metrics. Subsections provide in-depth detail about the production of virtual reality videos for the choice question, the survey design and results, estimation of the LCCM, and, lastly, an example of how an LCCM can be applied to construct a BLOS measure.

Literature Review

Introduction

Level of Service (LOS) is an objective measure for assessing roadway quality and performance. The resulting score typically provides a human interpretable value (e.g., a letter grade A-F) for practitioners and policy makers to determine resource allocation and investment. Historically, roadway LOS was primarily concerned with traffic flow and roadway capacity. As a result, many roads are designed with the purpose of maximizing vehicle throughput – with safety, comfort, and attractiveness as an afterthought. For pedestrians and bicyclists not securely seated in an automobile, service quality thus depends more heavily on user preferences related to safety and comfort than directly measured values as traffic speed and flow. This makes assessing bicycle level of service (BLOS) more complex, and more dependent on hard to measure qualitative values.

For over a half-century, traffic engineers in the United States have relied on the Highway Capacity Manual (HCM) for assessing roadway quality. Historically, the HCM was primarily concerned with traffic flow and capacity, but starting with the 6th edition of Highway Capacity Manual in 2010 (HCM) [1, 2], a multi-modal level of service (MMLOS) methodology was introduced that provides separate LOS estimates for automobiles, bicycles, transit users, and pedestrians [1, 3]. While this addition represented a huge paradigm shift for the HCM, the MMLOS methodology is now over a decade old and lacks many contemporary bicycle infrastructure treatments (e.g., separated lanes and bike boxes) and technologies available. Given the diversity of cities and their needs across the United States, a growing number of alternative LOS evaluation methodologies have been developed. However, these alternative methodologies employ a range of different data sources, estimation procedures, and scoring systems that focus on different scales (street-level vs network-level) or different aspects (e.g., attractiveness or safety). It is crucial to fully understand the strengths and weaknesses of each method when deciding between or developing a new BLOS methodology.

There exists an extensive body of literature regarding the multitude of factors that affect bicyclist travel demand, infrastructure, and network performance measure evaluation. To organize and prioritize the literature, it can be divided into two types:

- Investigative studies, and
- Repeatable methodologies

Investigative studies have the purpose of generating bicycle infrastructure evaluation results, typically using data for a specific location, and are generally produced by academics or industry consultants. While providing valuable insight and identifying key features and factors, these studies are generally a one-time effort and not intended to provide a generalizable "practice ready" methodology. In contrast, repeatable methodologies are intended to provide a generalized and repeatable methodology for evaluating bicycle level of service. These methodologies are often developed under the direction of public entities (e.g., cities, states, or governing research bodies) or interested activist groups. This research will focus on the latter but utilize the former for insights.

The remaining sections are organized as follows. First a discussion of key features and factors identified from the literature, but primarily from investigative studies. The next section then provides an overview of bicycle level of service methodologies, but focuses further on two prominent methodologies, Level of

Traffic Stress (LTS) and the Highway Capacity Manual's (HCM) Bicycle Level of Service (BLOS) methodologies. The next section provides a broad overview of survey methods used for BLOS calibration, followed by an overview of bicycle simulators. Last is a brief summary of literature findings.

Bicyclist Preferences

Objective safety is an important goal for transportation planners and engineers designing roadway facilities for bicyclists. At the same time, perception of safety and comfort can be barriers for many bicyclists choosing where or whether to ride [4]. Actual and perceived safety, however, are not always aligned [5], so it is important to keep both in mind in order to promote both the safety and prevalence of bicycling. While objective safety can be evaluated using collision data, perceptions of safety and comfort are often evaluated using stated or revealed preference survey methods. Bicycle level of service measures can then relate observable attributes of the roadway environment to subjective measures of comfort or safety from these surveys.

It is fairly well established that most bicyclists prefer riding in a bicycle lane [6] and are more likely to ride if bicycle facilities are provided [7, 8]. Newer advances, including buffered and protected bicycle lanes, are even more strongly preferred [9] as greater passing distance or physical separation between motor vehicles and bicyclists can significantly increase level of comfort for bicyclists [10, 11]. Female riders, more risk averse than male riders, tend to prefer maximum separation from motorized traffic [12]. In general, there can be a variety of bicyclist preferences depending on their bicycling level and purpose (e.g., leisure, commuting, or fitness), but a bicycle network should be convenient (comfortable, flexible, and efficient) and with minimal exogenous restrictions (e.g., danger, vandalism, and facilities) [13].

To build an effective bicycle network, it is important to understand the factors that affect the decision to ride a bicycle or not. Among the many factors that affect bicyclist preferences, they can be broadly classified into three types: S*ocio-behavioral* factors, which are specific to the bicyclists themselves, such as skill and confidence. *Environmental* factors, which are exogenous factors that cannot be controlled, such as weather and daylight. Lastly, *infrastructure and amenities* factors, which are environmental factors that can be controlled, such as bicycle lane or bicycle parking.

Socio-behavioral

Bicycling, unlike other modes, is not only affected by an individual's preferences and perceptions, but also their physical ability and confidence. The decision to bicycle is often a complex one that goes beyond simply travel-time and cost. The City of Portland developed an often cited typology of four cyclists types: *The Strong and the Fearless*, *The Enthused and Confident*, *The Interested but Concerned*, and *No Way No How* [16, 17]. Further studies have shown that more frequent bicyclists possess greater hazard anticipation levels than infrequent bicyclists [18]. Though simplistic, the importance of this typology is that when considering potential bicyclists, perception of safety can have a greater impact on different riders than statistical safety levels [19–21]. Numerous studies highlight importance of cultivating a robust bicyclist friendly community to collectively promote safe cycling, citing the "safety in numbers phenomenon" [22, 23].

Beyond a simple bicycling "confidence" metric, bicyclist preferences can vary by group. For example, an equally confident neighborhood bicyclist with young children will have different preferences than their urban commuting counterparts. Hosford et al. (2020) [24] found that while the Geller typology is intuitive, the categorization does not necessarily capture how bicyclists perceive themselves or their abilities. Thus, it is important to categorize bicyclists using latent characteristics as much as possible, rather than stated ability. A study by Griswold et al. (2017) [14, 15] utilized a Latent Class Choice Model (LCCM) to simultaneously define bicyclists groups and their preferences in a choice model. Such a model shows promise in accounting for empirical bicyclist preferences and bicyclist heterogeneity as well.

Environmental

Many studies have been conducted to investigate how weather and climate affect bicycle ridership dating back to the 1980's [25]. Studies use a variety of methods and data sources to measure factors affecting seasonality. Data sources include travel surveys [26, 27], personal interviews [28], bicycle count data [29–31], and more recently bike-share data [32]. Most methods are regression based with a varying degree of complexity. Ranging from simple multivariate regression, to autoregression and time-series models [33–35], and even machine learning techniques [36, 37]. The studies have successfully identified many environmental factors that affect bicycle ridership, such as temperature, precipitation, and daylight hours.

Temperature is a factor often identified in the literature as affecting seasonal ridership. It provides a convenient quantitative measure to evaluate ridership against. However, temperature itself is relative, its impact can vary from place to place, meaning that bicyclists in different locations may have different sensitivities or “cold hardiness”, but also season to season. [28, 38, 39]. Moreover, it has also been found that ridership is not linearly proportional to temperature, nor continuously increasing. Meaning that bicyclists are sensitive to both extreme heat as well as cold [40]. In addition to a temperature, several other environmental factors, such as precipitation, wind, and humidity affect bicycle demand [41–45].

Although it is to be expected that many “fair weather” bicyclists will cease bicycling during winter, a substantial number of bicyclists can still be found on roadways. Canada and many Northern European countries have achieved a great deal of success in maintaining year-round population of bicyclists [46]. Much of this success can be attributed to simply keeping bicycle routes open. Just as snow removal and lighting are essential to providing safe and efficient operation for automobiles, the same applies for bicycles [47–49].

Infrastructure and amenities

To mitigate safety and comfort factors affecting bicyclists, cities can provide certain infrastructure and amenities. The most obvious mitigation effort is to help improve safety through bicycle-specific infrastructure. Implementing bicycle infrastructure has been shown to result in an increase in overall bicycle ridership [7, 50, 51].

Bicycle infrastructure can range from simple “bicycle route” signage to physically separated lanes for bicycles [52]. Given existing roadway geometries with wide shoulders, standard bike lanes with white pavement striping tend to be most common due to their low cost, but novel designs with enhanced safety are continually created. The National Association of City Transportation Officials (NACTO) publishes several useful and in-depth guides for implementing bicycle infrastructure in urban settings [53] and the Massachusetts Department of Transportation (Mass DOT) was the first state DOT to publish official guidelines for separated bicycle lanes [54].

Early bicycle infrastructure focused on linear mid-block segments, but intersections are often the most dangerous section for bicyclists [55–58]. This has led to the development of innovative intersection designs for bicycle infrastructure, such as bike boxes and bicycle-specific signals [59–61]. However, it is critical to point out that isolated infrastructure, no matter how robust, should be incorporated into a higher-level network hierarchy [62–65].

Bicycle-specific infrastructure may address on-road comfort and safety concerns for bicyclists, but it is just one physical mitigation approach. Other approaches exist, such as navigational signs, winter snow removal and lighting, but also simply secure bicycle parking. For professional office working bicycle commuters, hygiene is a critical concern. To mitigate this, some employers provide showers and changing rooms for employees that commute by bicycle [66, 67]. Although potentially costly, it is arguably cheaper than providing transit reimbursements or constructing parking facilities [68].

Performance measures

Among the prominent bicycle performance measure methodologies, or BLOS methodologies, there is the San Francisco's Bicycle Environment Quality Index (BEQI) [69], Charlotte Urban Street Design Guide (CUSDG) [70], [Bicycling] Deficiency Index (DI) [71], and the Level of Traffic Stress (LTS) [72–74]. A paper by Zuniga-Garcia et al. [75] provides a thorough comparison of each methodology and the features covered in each, summarized in Table 1.

Table 1. Summary comparison of MMLOS methodological approaches*

Mode	Characteristic	HCM / TCQSM	CUSDG	BEQI / PEQI	LTS	BCI	DI
Bicycle	Auto volumes	X		X		X	
	Auto speeds	X	X	X	X	X	
	Percentage of heavy vehicles	X		X		X	
	Percentage of on-street parking	X		X	X	X	X
	Pavement rating	X		X			X
	Presence of bicycle lane or paved shoulder	X	X	X	X	X	X
	Width of bicycle lane	X		X	X		X
	Width of outside lane	X	X		X		X
	Bicycle lane blockage				X		
	Presence of physical barrier and buffers				X		
	Intersection crossing distance	X	X				
	Right-turns on red	X	X	X		X	
	Right-turn Lane length				X		
	Traffic calming features			X			
	Bicycle parking			X			
	Connection to on-street lanes		X	X			
	Line of sight, street slope, lighting			X			
	Residential development					X	
	Retail development			X			
	Street slope			X			
	Auto, transit, and pedestrian impact						X

*Original table in Zuniga-Garcia et al. [75]

Despite the thorough summary matrix provided by Zuniga-Garcia et al. [75], the comparison lacks depth of discussion on how these features are measured and scored. While all methods effectively determine a numeric score (e.g., 0-5 or 0-100) that can then be binned into a corresponding step function (e.g., LOS A-F) for evaluation, the scores themselves are calculated with very different approaches. The different methodological approaches can be categorized into three approach types:

- **Direct Classification** – Roadways/intersections are assigned a classification scale (e.g., 1-5) directly from a strict set of roadway feature criteria or standards.
- **Point system** – Each roadway feature is given a point value that contributes to the overall score that is either summed or averaged

- **Model-based** – A set of calibrated modeling functions are used to achieve a score based on input variables.

Point systems have weights assigned to each discrete feature and model-based functions will have weights embedded as constants to calibrate the functions to the expected level of service. Although direct classification may not have explicit weights, the pre-defined bins effectively provide a weighting bias to the eventual score.

Direct classification and point-based systems tend to be simpler and more intuitive compared to model-based approaches, which typically utilize some regression-based calibration. Direct classification methods also tends to be more conservative, often using a "weakest link" approach where the score is based on the worst parameter [73]. This ensures that critical factors are not ignored, such as extreme traffic speeds and volumes, but also fails to account for mitigating factors, such as separated facilities.

In any approach, the score calculation is calibrated using some weighting value to assign greater importance to certain features or situations. These weights are determined either by:

- **Expert defined** – Weights assigned *a priori* by creators as they see fit.
- **Empirical** – Weights determined *a posteriori* through measurements and surveys.

Empirical weights provide a more realistic and reliable "ground truth" but require extensive research and analysis studies to calibrate the values. Expert defined values are simply assumed by the methodological designers, often with the intent of being simpler and easier to implement. Expert defined methods also tend to be more conservative, providing aspirational guidance for fostering a robust bicycling culture rather than pegging results to current bicyclist preferences.

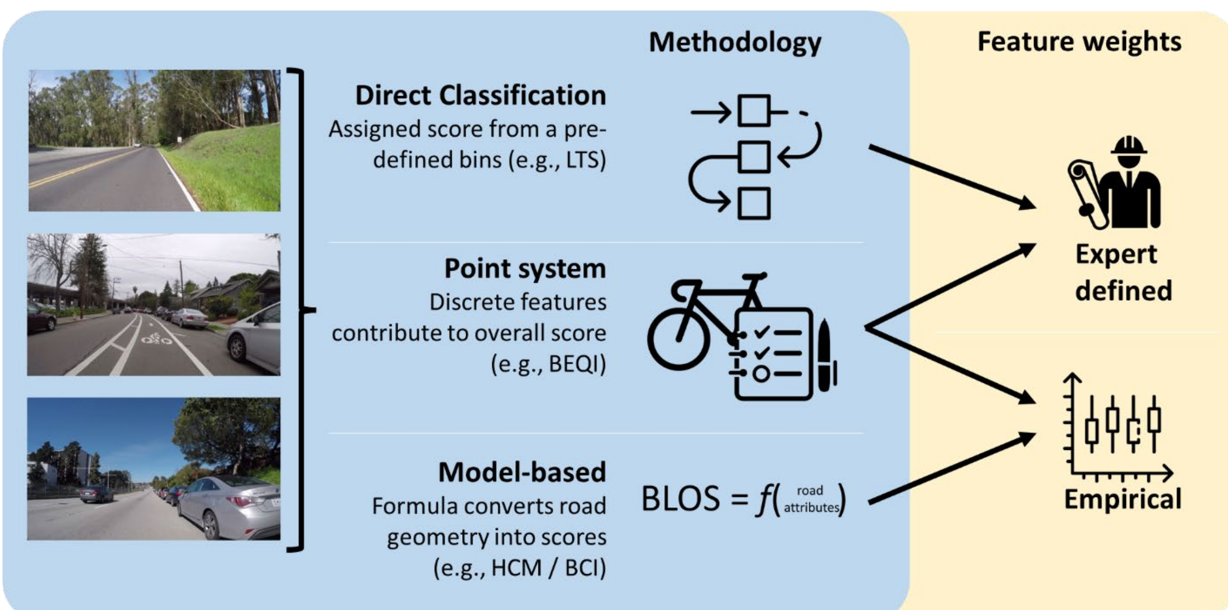


Figure 1. Diagram of methodological and feature weighting approaches

Over the last three decades, many BLOS-type measures have been developed and continue to be developed. A summary comparison of common BLOS methodological approaches and their pros/cons are shown in Table 2. These methodologies range from generalized approaches that are applicable anywhere, such as the HCM BLOS, Deficiency Index, and LTS; to robust but specialized tools for specific cities like the San Francisco BEQI and Charlotte USDG.

Table 2. Summary Comparison of MMLOS Methodological Approaches

Method	Approach	Calibration	Pros	Cons
Bicycle Environmental Quality Index (BEQI)	Additive	Empirical	• Evaluates intersection and links • Easy to apply	• Weak bicycle intersection assessment • Many equal weighted/uncalibrated attributes
Deficiency Index (DI)	Averaged	Empirical	• New features easily added • Interaction of modes	• Requires technical knowledge • Requires a survey of stakeholders • Subjective scales of application
Highway Capacity Manual (HCM BLOS)	Model-based	Empirical	• Evaluates intersection and links • Strong research background • Objectively measured inputs	• Complex and not easy to apply • Requires detailed data collection • Lacks attractive/comfort features • Not easily re-calibrated
Bicycle Compatibility Index (BCI)	Model-based	Empirical	• Easy to apply • Minimal field measurement	• Does not evaluate intersections
Level of Traffic Stress (LTS)	Direct Classification	Expert	• Easy to apply • Evaluates intersection and links • Network level focus • Minimal field measurement	• Requires substantial GIS data • Lacks multicriteria mitigation
Charlotte Urban Street Design Guide (CUSDG)	Additive	Expert	• Easy to use • Detailed assessment	• Does not evaluate link segments • Locally subjective
Walk / Bike Score	Model-based	Empirical	• Easy to apply • No data collection • Evaluates intersection and links	• Not sensitive to infrastructure deficiencies (e.g., lack of bicycle lane or sidewalk) • Proprietary data and methodology

Although an ever-growing variety of bicycle performance measure methodologies exist, two methodologies remain prominent among commonly used methodologies:

- Highway Capacity Manual's Bicycle Level of Service (HCM BLOS) methodology, and
- Level of Traffic Stress

The two methodologies offer very different approaches and outcomes, which are explained in further detail in the following subsections.

Bicycle Level of Service

The HCM's BLOS methodology is an empirically calibrated model-based approach. It is based upon several levels of nested mathematical functions each calibrated to empirical bicyclist preferences. The methodology is organized into three spatial components, links, intersections, and segments.

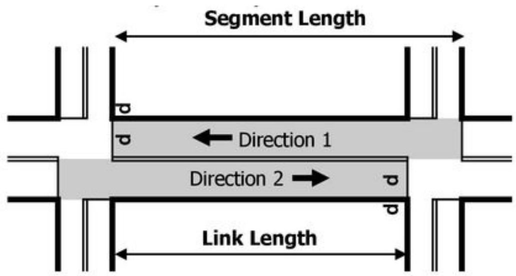


Figure 2. HCM link, intersection, and segment definition diagram

Links are the linear sections between intersections and segments are formed by the combination of contiguous links and intersections. Links and intersections receive a separate LOS score, which are calculated through various adjustment factors, which are then inputted into a subsequent function for segment LOS:

- *Segment:* $I_{b,seg} = 0.160 I_{b,link} + 0.011 F_{b,link} e^{I_{b,int}} + 0.035 \frac{N_{ap,s}}{L/5280} + 2.85$ (1)
- *Link:* $I_{b,link} = 0.760 + F_{wL} + F_v + F_s + F_p$ (2)
- *Intersection:* $I_{b,int} = 4.1324 + F_{wI} + F_v$ (3)

where:

I is the LOS score (0 = A and 5 = F) for links, intersections, and segments, respectively;
F_v is motorized vehicle volume adjustment factor,
F_s is motorized vehicle speed adjustment factor,
F_p = pavement condition adjustment factor,
F_{delay} is bicycle delay adjustment factor,
$F_{wL} = -0.005 W_e^2$ is link cross-section adjustment factor where W_e is the effective width, and
$F_{wI} = 0.0153 W_{cd} - 0.2144 W_t$ is intersection cross-section adjustment factor. W_t is the total width of the outside through lane, bicycle lane, and paved shoulder; W_{cd} is the curb-to-curb width of the cross street.

There are a variety of sub-equations and variables, but the critical features in the HCM BLOS model are street cross-section width, pavement quality, traffic speed, and traffic volume. Although the HCM's BLOS model is robust with a strong research background, it has several shortcomings.

The current version of the HCM does not account of bicycle delay and traffic speed for intersection LOS, nor does it include separated bike lanes for link LOS. This lack of bicycle delay and traffic speed at intersections is problematic as it implies that when designing intersections, bicycle delay can be ignored, and high-speed traffic is not a concern for bicycles. Although traffic speed is accounted for at the link level (i.e., midsegment), it offers no mitigating features (e.g., separated bike lanes) and ignores the fact that automobiles can still travel through an intersection at high-speed, which often is where most bicycle-vehicle crashes occur.

Most shortcomings are largely addressable through revisions to the HCM, but a more critical challenge to the HCM's BLOS methodology are the data and calculation intensive requirements. The HCM's BLOS methodology is an eight-step process with over a half-dozen different equations and nested sub-equations described across multiple chapters for urban street segments and intersections [2]. Ultimately, the requirements and complexity limit the scale to which the methodology can be feasibly applied, making it more narrowly applicable to smaller project-level scale where field data can be obtained, rather than a broader network-level focus.

Level of Traffic Stress

In contrast to the HCM's BLOS methodology, the LTS methodology is much more simplistic and intuitive. The current version consists of just three primary tables shown in Tables 3-5 which are used depending if the road segment is mixed traffic, has a bike lane not adjacent to parking, or has a bike lane adjacent to parking [74, 76]. The criteria selection procedure used a "weakest link" principle, which assumes that the worst performing criteria dictates the level of traffic stress. For example, an unlaned 2-way street with a prevailing traffic speed of 50+ mph and an Average Daily Traffic (ADT) volume of less 750 vehicles per day will receive an LTS rating of 3, despite having a very low ADT.

Table 3. LTS Version 2.0 Criteria for Mixed Traffic Road Segments [77]

		Prevailing Speed						
Number of lanes	Effective ADT*	≤ 20 mph	25 mph	30 mph	35 mph	40 mph	45 mph	50+ mph
Unlaned 2-way street (no centerline)	0-750	LTS 1	LTS 1	LTS 2	LTS 2	LTS 3	LTS 3	LTS 3
	751-1500	LTS 1	LTS 1	LTS 2	LTS 3	LTS 3	LTS 3	LTS 4
	1501-3000	LTS 2	LTS 2	LTS 2	LTS 3	LTS 4	LTS 4	LTS 4
	3000+	LTS 2	LTS 3	LTS 3	LTS 3	LTS 4	LTS 4	LTS 4
1 thru lane per direction (1-way, 1- lane street or 2-way street with centerline)	0-750	LTS 1	LTS 1	LTS 2	LTS 2	LTS 3	LTS 3	LTS 3
	751-1500	LTS 2	LTS 2	LTS 2	LTS 3	LTS 3	LTS 3	LTS 4
	1501-3000	LTS 2	LTS 2	LTS 3	LTS 3	LTS 4	LTS 4	LTS 4
	3000+	LTS 3	LTS 3	LTS 3	LTS 3	LTS 4	LTS 4	LTS 4
2 thru lanes per direction	0-8000	LTS 3	LTS 3	LTS 3	LTS 3	LTS 4	LTS 4	LTS 4
	8001+	LTS 3	LTS 3	LTS 4	LTS 4	LTS 4	LTS 4	LTS 4
3+ thru lanes per direction	any ADT	LTS 3	LTS 3	LTS 4	LTS 4	LTS 4	LTS 4	LTS 4

* Effective ADT = ADT for two-way roads; Effective ADT = 1.5*ADT for one-way roads

Table 4. LTS Version 2.0 for bike lanes and shoulders not adjacent to a parking lane [77]

		Prevailing Speed					
Number of lanes	Bike lane width	≤ 25 mph	30 mph	35 mph	40 mph	45 mph	50+ mph
1 thru lane per direction, or unlaned	6+ ft	LTS 1	LTS 2	LTS 2	LTS 3	LTS 3	LTS 3
	4 or 5 ft	LTS 2	LTS 2	LTS 2	LTS 3	LTS 3	LTS 4
2 thru lanes per direction	6+ ft	LTS 2	LTS 2	LTS 2	LTS 3	LTS 3	LTS 3
	4 or 5 ft	LTS 2	LTS 2	LTS 2	LTS 3	LTS 3	LTS 4
3+ lanes per direction	any width	LTS 3	LTS 3	LTS 3	LTS 4	LTS 4	LTS 4

Notes:
1. If bike lane / shoulder is frequently blocked, use mixed traffic criteria.
2. Qualifying bike lane / shoulder should extend at least 4 ft from a curb and at least 3.5 ft from a pavement edge or discontinuous gutter pan seam.
3.Bike lane width includes any marked buffer next to the bike lane.

Table 5. LTS Version 2.0 Criteria for Bike lanes alongside a parking lane [77]

		Prevailing Speed		
Number of lanes	Bike lane width	< 25 mph	30 mph	35 mph
1 lane per direction	15+ ft	LTS 1	LTS 2	LTS 3

	12-14 ft	LTS 2	LTS 2	LTS 3
2 lanes per direction (2-way)	15+ ft	LTS 2	LTS 3	LTS 3
2-3 lanes per direction (1-way)		LTS 2	LTS 3	LTS 3
other multilane		LTS 3	LTS 3	LTS 3

Notes:
1. If bike lane is frequently blocked, use mixed traffic criteria.
2. Qualifying bike lane must have reach (bike lane width + parking lane width) > 12 ft
3.Bike lane width includes any marked buffer next to the bike lane.

The LTS methodology is elegantly simple to implement and has relatively minimal data input requirements. This has made it immensely popular among city and regional departments of transportation (DOTs), but it does have some considerations and limitations.

One consideration is that LTS is a non-empirical, expert defined, method. The criteria bins and score are defined by the creators and do not necessarily reflect bicyclists' preferences. Although it can be argued that the results are intended to act as robust design standards to promote bicycling and improve safety, this ultimately limits its potential applications, such as in any predictive demand or route choice models.

Another limitation of LTS is it only has limited support for intersections. As shown in Table 6 and Table 7, the LTS method only covers a narrow range of possible intersection configurations and clearly favors unsignalized crossings where the best possible LTS score for a signalized intersection is LTS $\geq$ 2. Neither Table 6 nor Table 7 account for a variety of other intersection criteria, such as traffic volume, number of signalized lanes, approaches, signal phasing, or intersection treatments (e.g., bike boxes or curb separations.), etc.

Table 6. LTS Version 2.0 Criteria for Bike Lanes and Mixed Traffic on Intersection Approaches in the Presence of a Right Turn Lane [77]

Configuration	Level of Traffic Stress
Single right-turn lane up to 150 ft long, starting abruptly while the bike lane continues straight; intersection angle such that turning speed is ≤ 15 mph.	LTS ≥ 2
Single right-turn lane longer than 150 ft, starting abruptly while the bike lane continues straight; intersection angle such that turning speed is ≤ 20 mph.	LTS ≥ 3
Single right-turn lane in which the bike lane shifts to the left, but intersection angle and curb radius are such that turning speed is ≤ 15 mph.	LTS ≥ 3
Single right-turn lane with any other configuration; dual right-turn lanes; or right-turn lane plus option (through-right) lane.	LTS = 4

Table 7. LTS Version 2.0 Criteria for Unsignalized Crossings [77]

		Width of Street Being Crossed		
	Speed Limit or Prevailing	Up to 3 lanes	4-5 lanes	6+ lanes
NO CROSSING ISLAND	Up to 25 mph	LTS 1	LTS 2	LTS 4
	30 mph	LTS 1	LTS 2	LTS 4
	35 mph	LTS 2	LTS 3	LTS 4
	40+	LTS 3	LTS 4	LTS 4
WITH CROSSING ISLAND	Up to 25 mph	LTS 1	LTS 1	LTS 2
	30 mph	LTS 1	LTS 2	LTS 3
	35 mph	LTS 2	LTS 3	LTS 4
	40+	LTS 3	LTS 4	LTS 4

The primary limitation of the LTS method is that the weakest link approach does not allow for multi-criteria mitigation effects. For example, a high-speed and high-volume road segment with a separated bicycle lane with a vertical buffer (e.g., bollards) would still receive a poor LTS score despite having robust bicycle infrastructure. Although the simple weakest link offers ease of implementation, it ultimately limits the methodology's ability to account for these nuanced mitigation effects.

Survey methods

Conventionally, empirical level of service measures and other user preference measures are typically calibrated using some form of survey data. Quantitative preferences are then determined either through simple aggregation of response frequency, or through more sophisticated econometric regression-based models that can extract intangible taste preferences [78–83]. A major challenge with form-based survey data sources is that they ultimately rely on a person's stated preference in a hypothetical scenario rather than capturing their revealed preference from their observed behavior [84]. This can potentially introduce bias due to personal opinions and activist behavior. For example, respondents may want to promote bicycle lanes, so they respond overly positive to bicycle lanes. While revealed preference data is preferred, it is often not feasible, making stated preference surveys a valuable tool. For example, a study to estimate use of a future product or service cannot capture observed behavior for something that does not yet exist.

In addition to the structural challenged of stated versus revealed preference, there is often an unconscious bias between the imagined and real experience. For example, a respondent may feel that riding a certain route was not as bad when experienced in real life compared to when presented with a hypothetical scenario. Researchers have attempted to mitigate this by increasing the immersive experience of surveys from simple written descriptions and still images, all the way to handlebar mounted video footage or helmet mounted camera videos [14, 15]. However, despite these efforts, Fitch and Handy (2018) showed that there still exists a systematic 10-15% error between video-based survey of bicycle trips and when actually ridden.

Although video provides a substantially improved experience over static surveys, the narrow field of view (i.e., computer screen) and lack of any other sensory input limits the overall experience (e.g., wind, pedaling, proximity sensation of passing vehicles, etc.). Portable lightweight cameras often utilize wide-angle lenses in order maximize the field of view in a compact form. While ideal for cinematic purposes, this distorts the actual dimensions of objects in the scene. For example, distance to passing vehicles or dimensions of bicycle lanes will differ from reality. Moreover, handlebar and helmet mounted cameras are often prone to "camera shake" and distortions from exaggerated road vibrations. While modern stabilizers and post-production editing can reduce camera shake, it can still be distracting or even cause motion sickness to viewers. Ultimately, there still exists a substantial experiential gap between the imagined experience and a real experience with video-based survey techniques.

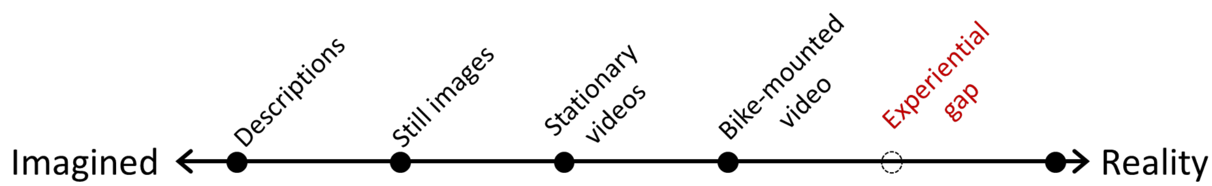


Figure 3. Experiential spectrum of imagined and real survey experience

This experiential gap can, however, be filled with virtual reality (VR) technology. Although VR is still not reality, it can substantially close the gap without putting researchers and participants in any dangerous situations. Moreover, VR also offers the added research benefit of providing complete environmental control to researchers. Unlike video-based survey methods where a representative case must be found and filmed, with no control over traffic volumes or other conditions, a simulated environment can be developed with precise land use context, lane dimensions, features, and even traffic conditions.

Virtual reality & simulation

In recent years, VR has accelerated from a novel technology primarily for entertainment purposes, to an industry spanning tool with applications ranging from research, prototyping, and training. Although the headset display is a significant breakthrough in simulation technology, immersive simulation is a mature field of science firmly rooted in a human factors and psychology.

Although a more primitive training apparatus could arguably be considered a simulator, the earliest recognized simulation device were mechanical flight simulators developed in the early 20th century [86, 87]. Lacking modern audio-video media capabilities, they were primarily focused on providing a tactile interface for training pilots on the ground. Flight simulators steadily evolved from simple mechanical devices to sophisticated computerized flight simulations and moving platforms with 6-degrees of freedom [88]. In the late 20th century, the automotive industry began developing their own driving simulators for industry (e.g., prototype mock-ups, safety, and even insurance-related research). These simulators typically consist of a stationary vehicle with a roadway environment projected in front of the vehicle [87].

These driving simulators eventually branched into other modes, such as trains, bicycles, and even pedestrians. However, bicycles and pedestrians present a unique challenge in connecting the movement controls (e.g., pedals and walking) to the simulated environment. This was typically solved using a "CAVE" Automatic Virtual Environment, in which users wear 3D glasses that not only provide stereoscopic display, but also track the user's movements in the environment [89, 90]. Although feasible, the elaborate system limits use to all but the most dedicated and funded research facilities.

With the rapid advancement and increasing affordability of commercially available VR technology over the last decade, a growing number of research-based bicycle simulator labs set up around the world. Headset-based VR systems not only solve the perception of distance more easily [91], but offers several other advantages over traditional CAVE-based systems:

- **Simplicity:** Rather than a computing cluster for support multiple fixed projection screens in a CAVE system, VR requires only a single computer and headset display unit to achieve fully omnidirectional display.
- **Cost:** Simpler VR systems generally translate to cheaper overall system costs compared to complex CAVE-based systems with proprietary parts and software.
- **Flexibility:** VR is no longer constrained to a dedicated CAVE facility and can be scaled to a room of almost any size.
- **Community Support:** There exists a large development community populated by a variety of professions that offers greater support and more development software options, not just proprietary software used by niche industry professionals or academic research.
- **Enhanced data collection**: VR offers a variety of unique or native data collection options, such as eye tracking, head movement, and other measurement capabilities integrated into headsets directly.

However, VR-based simulation is still a relatively new research apparatus and has not yet reached the mature level of institutional acceptance that other more established systems have. Validation studies found that bicycle VR provides statistically reliable results for most measures, such as lane position, passing distance, head movements, and acceleration; but found some measures still require further calibration in some cases, such as speed [91, 92]. Still, the ever growing and advancing field of VR continues to gradually gain acceptance as a scientific tool providing a promising research method for evaluating a variety of psychological or human factors-oriented questions regarding bicycling and bicycle infrastructure [93–96].

Much like historical simulator research, there are two main veins in this simulator research: simulators that focused on recreating the *physical* tactile realism of riding a bicycle on the road for the purpose of safety or other training [97–101], and simulators that focused on *visual* immersive realism for the study of perceptions of infrastructure or bicyclist behavior [94, 102–107].

Summary

Despite evidence that empirical measures do a better job of predicting route choice [108, 109], level of traffic stress (LTS) [74, 76] has become one of the most commonly applied measured in the United Sates. Its popularity is due to the minimal data requirements and ease of interpretation which relies on an elegantly simple “weakest link” principle in which the final score is determined by the worst scoring criteria in a rubric. This ease of use and minimal data requirements of LTS also make it well suited for network-level implementation. In contrast, the HCM’s BLOS methodology is much better suited for more detailed project-level applications but has very intensive data requirements by comparison. However, the LTS methodology has limited support for intersections and lacks multi-criteria mitigation effects (e.g., separated bike lanes to mitigate traffic speed and volume). Currently neither LTS nor HCM’s BLOS account for the safety and comfort benefits provided by vertical separation or protection of bicycle facilities [110], but the HCM’s BLOS method’s model-based approach can be revised to offer multicriteria mitigation effects.

An ideal BLOS methodology for California’s State Highway System would incorporate elements from both methods. An empirical method robust enough to account for bicyclist preferences and heterogeneity, making the methodology usable for both level of service and traffic stress, but also potentially in simple route choice and other network-level models. However, the methodology should also be a simple approach with minimal data requirements that can be feasibly deployed across large geographic areas, such as a Caltrans district or even statewide.

To develop an empirically calibrated methodology, a survey study is required. However, in addition to the experiential gap inherent to video-based surveys, there is the experimental design challenge of finding and filming sufficient representative cases to estimate the model for all desired variables (e.g., bicycle lane type, traffic conditions, land use context, etc.). It is also possible that some desired features may not yet exist, such as certain separated bicycle lane facilities. To overcome these challenges, a VR-based bicycle simulator enables researchers to build precise environmental simulations while achieving a vastly improved immersive experience.

Methodology Overview

This project seeks to unveil distinct bicyclist groups and biking preferences among Californians by integrating two innovative methodologies in BLOS development: a Latent Class Choice Model (LCCM) and Virtual Reality (VR) simulation. VR-based videos are incorporated into a stated preference survey, which captures individuals' biking preferences, and which in turn serve as inputs for the modelling process.

The focus of the project revolves around understanding biking preferences specifically related to the availability of bike infrastructure (e.g. marked bike lanes, protected bike lanes, buffers), traffic conditions, and road surface conditions. The project is structured into four parts:

1. Design of the VR scenarios
2. Design of the stated preference survey
3. Model estimation
4. BLOS development

The subsequent sections provide comprehensive descriptions of the procedures utilized in each part.

Design of Virtual Reality Scenarios

The purpose of this task was to produce 30 virtual reality videos. The videos form the basis of the survey and are what allow us to capture individuals' biking preferences. The goal was to design VR scenarios showing roadway segments that resemble streets in the State Highway System and that include bike infrastructure that can be found in California. Each video is unique and shows different bicycle facilities and roads with varying degrees of traffic and surface conditions. The videos were created following a three-step process:

1. Variable Selection: Identifying the key variables that impact individuals' biking preferences and should be incorporated into the VR scenarios.
2. Orthogonal Design: Utilizing an orthogonal design to systematically vary the selected variables in a balanced and efficient manner, ensuring each video represents unique combinations of bike facilities and road conditions.
3. Virtual Scenario Development: Incorporating the chosen variable combinations to develop each VR video, resulting in a diverse set of scenarios for participants to evaluate during the stated preference survey.

Respondents were shown all thirty videos in random pairs. We considered that thirty videos (15 pairs) were sufficient to obtain enough choice answers from respondents without making the survey too long.

Variable Selection

To design roads that resemble the SHS, we referenced California roadway and bicycle facility design guidelines such as the CA MUTCD, the CA Highway Design Manual, the Design Information Bulletin 89-02 for Class IV Bikeway Design Guidelines, and Google Maps. We also referenced Caltrans' Traffic Census Program to inform the selection of traffic volumes and percentages of heavy duty vehicles. The virtual scenarios shown seek to recreate the following types of bike facilities that can be found in California:

1. Shared roadway

2. Class II Bikeway (bike lane with or without buffer)
3. Class IV Bikeway (separated bikeway)

To construct the above bikeways, two kinds of variables were considered: those that characterize traffic conditions and those that characterize the bike facility. The former includes variables such as traffic volumes and percentage of heavy duty vehicles on the road. The latter include variables such as bike lane width, buffer width, and barrier types. These variables can be combined to create all three of the bikeway types. The final list of design attributes and their corresponding values are shown in Table 8. These are considered independent variables in the modeling process.

Table 8. Scenario Design Attributes/Independent Variables

Variable Name	Description	Values
Context	Urban or rural setting	Rural one-lane per direction Urban one-lane per direction Urban multi-lane per direction
Traffic volume	Average Daily Traffic on road	Low: <= 3,000 Medium: 3,000 - 6,113 High: > 6,113
Speed	Vehicle speed on road	Low: 25 mph Mid: 40 mph High: 55 mph
Heavy-Duty Vehicle (HV) Proportion	Proportion of traffic volume that is heavy-duty vehicles	Low: 3% Mid: 6% High: 9%
Bike lane width	Width of the bike lane	0 ft (no bike land and no shoulder) 2 ft (no bike lane, only shoulder) 5 ft (one-way Class II; one-way Class IV) 8 ft (two-way Class IV)
Buffer width	Width of the buffer	0 ft (no bike lane and no shoulder) 3 ft 7 ft 11 ft (8 ft parking lane + 3 ft buffer)
Barrier height 1	Height of barrier	0 ft (no physical barrier) 0.5 ft (raised island) 3 ft (flexible or inflexible barrier)
Buffer height 2	Height of second barrier. Only applies when bike facility is a bike lane protected by a parking lane	0 ft (no physical barrier) 0.5 ft (raised island) 3 ft (flexible or inflexible barrier)
Pavement quality	Quality of bike lane pavement	Bad (many cracks) Good (some cracks) Perfect (smooth, no cracks)

Orthogonal Design

An orthogonal design was implemented to determine the combination of variables in Table 8 to be presented in each video. An orthogonal design, a type of fractional factorial design commonly used in stated preference surveys, ensures that all independent variables can be estimated independent from one another without exposing respondents to all possible variable combinations [111]. The final set of combinations, the estimated design matrix, is orthogonal, which is a property that ensures that the effect of any one variable is unconfounded with the effects of another.

Our experiment has 9 variables, each with at least 3 levels, amounting to nearly 19,000 possible combinations. With the orthogonal design we reduce the number of combinations to the predetermined number of 30, and the algorithm determines the necessary combinations to both capture the main effects of each attribute and to represent each attribute level equally. In that way, a bike lane width of 5 ft is equally represented as a buffer lane of 3 ft. Since all respondents are shown all 30 videos, we can are able to collect information on how individuals respond to all independent variables.

Prior to conducting the orthogonal design, unrealistic variable combinations were removed. For instance, scenarios where the bike lane width was 0 ft or 2 ft and the buffer width was anything but 0 ft were dropped, as it is unlikely that, in narrow roads, space would be devoted to a buffer and not to expand the width of the bike lane. Similarly, combinations were dropped if the bike lane width was 8 ft (which is the minimum for a two-way bike lane) and the buffer was 0 ft, as all two-way bike lanes are protected lanes per California guidelines. Similar unrealistic scenarios were excluded prior to running the orthogonal design.

Table 9 shows the results of the orthogonal design.

Virtual Scenario Development

The videos were created using a Virtual Reality (VR) environment empowered by Unity Engine (UE), with the interface developed based on SteamVR and Wahoo SDK. One of the advantages of VR lies in that it enables the development of scenarios where all design elements can be controlled. Therefore, all traffic conditions and bike infrastructure variables could be adjusted as required by the orthogonal design.

Thirty road segments were designed, each one representing one of the variable combinations listed in Table 9. The virtual world and its design elements (e.g. street furniture, cars, buildings) were selected to resemble Californian streets as much as possible. All videos show the full width of a road along with the buildings, sidewalks, and street furniture that are adjacent to it. The weather and position of the sun were also adjusted so as not to become elements of distraction for viewers. For instance, selecting a particular time of day in the world was crucial to eliminate sun glare and building shadows that may adversely affect viewers' experience while "riding" on the road. The videos also include the sound of vehicles passing by. The velocity of the car speed also impacts the loudness of the approaching vehicle.

Figure 4. Multi-lane urban road with protected bike lane

Figure 5. Multi-lane rural road with bike infrastructure

Once the scenarios were created, 10-second long videos were recorded to show the experience of riding a bike on that road segment. The camera was spatially positioned where the hypothetical biker would be riding and moved in a straight line along the road, as if the viewer were biking along the street. While the videos do not show the bike on which the viewer is riding on, the camera is placed at a certain height from the road to give the viewer the sensation that they are on a bike. Figures 4 and 5 show two screenshots of the VR scenarios.

Despite the meticulous precision with which the elements of the virtual world can be designed it still falls short of precisely replicating the real-world experience, resulting in a sensation more akin to being in a video game. This may have an unwanted effect on respondents' choice-making, potentially making viewers feel safer and more comfortable in the virtual setting compared to real-life street conditions, consequently impacting their selection criteria when determining which alternative to choose. This is something that needs to be considered when analyzing the data. Our team further investigates the validity of using VR videos by comparing results with a follow-up in-person experiment where participants are asked to ride on the bike simulator. Participants ride through the same pairs as the ones they were presented in the survey and asked to respond the same questions. Findings for this part of the experiment can be found in the Griswold 2022 STRP Report.

Table 9. Orthogonal Design Variable Combinations

No.	Context	Traffic volume	Speed	% Heavy Duty Vehicles	Bike Lane Width	Buffer Width	Barrier 1 Height	Barrier 2 Height	Pavement quality
1	Rural one-lane	High	Low	High	0ft	0ft	0ft	0ft	Perfect
2	Urban one-lane	Low	High	Mid	2ft	0ft	0ft	0ft	Perfect
3	Rural one-lane	Mid	Low	High	5ft	0ft	0ft	0ft	Perfect
4	Urban multi-lane	High	Mid	Mid	5ft	11ft	0ft	0ft	Perfect
5	Urban one-lane	Low	Low	Low	8ft	11ft	0ft	0ft	Perfect
6	Urban multi-lane	High	Mid	High	8ft	3ft	0.5ft	0ft	Perfect
7	Urban multi-lane	Low	Mid	Low	8ft	7ft	0.5ft	0ft	Perfect
8	Urban one-lane	Mid	Mid	Low	5ft	3ft	3ft	0ft	Perfect
9	Urban multi-lane	Mid	High	Mid	5ft	7ft	3ft	0ft	Perfect
10	Rural one-lane	Mid	High	Low	8ft	11ft	4ft	0.5ft	Perfect
11	Urban multi-lane	Mid	Mid	Mid	0ft	0ft	0ft	0ft	Good
12	Urban multi-lane	Mid	Low	Low	2ft	0ft	0ft	0ft	Good
13	Urban one-lane	High	Mid	Low	5ft	0ft	0ft	0ft	Good
14	Rural one-lane	Mid	High	Low	5ft	3ft	0ft	0ft	Good
15	Rural one-lane	Low	Mid	Mid	8ft	3ft	0ft	0ft	Good
16	Urban one-lane	Low	High	High	5ft	7ft	0.5ft	0ft	Good
17	Urban one-lane	Mid	High	High	8ft	11ft	0.5ft	0ft	Good
18	Urban one-lane	High	Low	Mid	8ft	7ft	3ft	0ft	Good
19	Rural one-lane	Low	Mid	Low	5ft	11ft	3ft	0ft	Good
20	Urban multi-lane	Low	Low	High	5ft	11ft	4ft	3ft	Good
21	Urban one-lane	Low	High	Low	0ft	0ft	0ft	0ft	Bad
22	Rural one-lane	High	Mid	High	2ft	0ft	0ft	0ft	Bad

No.	Context	Traffic volume	Speed	% Heavy Duty Vehicles	Bike Lane Width	Buffer Width	Barrier 1 Height	Barrier 2 Height	Pavement quality
23	Urban multi-lane	Low	High	Mid	5ft	0ft	0ft	0ft	Bad
24	Urban one-lane	Mid	Mid	High	5ft	7ft	0ft	0ft	Bad
25	Urban multi-lane	High	Low	Low	8ft	7ft	0ft	0ft	Bad
26	Urban one-lane	High	Low	Mid	5ft	3ft	0.5ft	0ft	Bad
27	Rural one-lane	Mid	Low	Mid	5ft	11ft	0.5ft	0ft	Bad
28	Urban multi-lane	Low	Low	High	8ft	3ft	3ft	0ft	Bad
29	Urban multi-lane	Mid	High	High	8ft	11ft	3ft	0ft	Bad
30	Urban one-lane	Mid	Mid	Mid	8ft	11ft	4ft	0ft	Bad

Stated Preference Survey

The survey was designed to capture people's stated preferences for bike routes along with self-reported socio-demographic data, bicycling experience and frequency, perceptions on level of skill or comfort on a bike, and preferred facility types. We aimed to capture responses from a large pool of Californians, with varying degrees of bicycling experiences and skill level. The survey was distributed online both in English and Spanish and shared with numerous cycling organizations. To incentivize participation, we had a drawing to give away gift cards. Additionally, to increase participation from underrepresented groups, we offered $10 gift cards to minority respondents. The survey was open from March 15, 2023 to May 5, 2023. A copy of the survey can be found in the Appendix.

Survey Design

The survey consisted of two sections. In the first section, respondents provided demographic information and details about their biking habits, including age, gender, ethnicity, riding frequency, and infrastructure preferences. The second section included the choice questions where respondents were asked to choose between pairs of VR videos. The survey was created in Qualtrics and takes approximately 15-20 minutes to complete. We only collected responses from people who were 18 years or older and knew how to ride a bike. Two screening questions were included at the start of the survey to make sure that respondents met these requirements.

The full survey is available in the Appendix. However, here we present some examples of questions that were asked. Aside from demographic questions, we incorporated statements for respondents to rate on a 5-level Likert scale. These include:

Rate each of the following statements based on how you agree or disagree (strongly agree – somewhat agree – indifferent – somewhat disagree – strongly disagree):

1. I like riding bicycle
2. I would like to ride a bicycle more than I currently do
3. I am satisfied with the availability of on-street bicycle facilities like bike lanes, buffered bike lanes and protected bike lanes
4. I would bicycle more if it felt safer and more comfortable
5. Bicycling is a high-risk activity

Rate each of the following factors based on how important they are to you when selecting your bicycle route (extremely important - very important – moderately important – slightly important - not important at all):

1. Roads with low speed traffic
2. Most direct path
3. Marked bike lanes
4. Avoiding crime
5. Not steep/hilly

Rated responses help us capture not only concrete responses but also abstract feelings or concepts surrounding biking and the biking environment. They offer data for exploring latent preferences that may not be explicitly stated in the survey and can help identify the latent classes within the LCCM.

The second section included the choice questions. Here, respondents were presented with two random videos from the pool of thirty, fifteen times. Each respondent was presented with different pairs of videos.

Respondents were asked to watch the videos and answer the following question:

"Imagine you are riding a bike to a specified destination. There are two routes you can take, each with different road characteristics: route A (video A) and route B (video B). Travel time to your destination is the same for both routes."

Route A

Route B

If you had to choose one option for your trip, which would you choose?

A. Definitely Route A
B. Probably Route A
C. Indifferent
D. Probably Route B

E. Definitely Route B

If these were the only two options available, would you choose to ride a bike?

F. I would not ride a bike
F. I would ride a bike

The last question serves as the opt-out option and was included as a follow-up to the choice question to prevent the loss of valuable information regarding people's preferences, which might have occurred if an opt-out was provided as an additional third option.

The data collected from the survey formed the foundation for estimating the Latent Class Choice Model: responses to the choice questions are the dependent variables and all other questions serve as independent variables that help characterize the respondents.

Survey Dissemination

We sought to reach as many Californians as possible and to include groups that are typically underrepresented in research. To this end, we contacted multiple California bicycle advocacy groups and cycling clubs based in areas all across the state. To encourage the participation of underrepresented communities we partnered with Poder, a grass-roots organization that works with Latino immigrants and other minorities like Black, indigenous and other low-income communities of colors. We designed flyers that included a description of the research project and the link to the survey in English and in Spanish. We then sent the flyers via email to the organizations and asked them to forward the flyers to their mailing lists. In addition to sharing the flyers with Poder, we also set up two iPads with the survey to have at the Poder office. Members who visited the office were encouraged to take the survey. Finally, the survey was also shared with the SafeTREC mailing list. Part of the mailing list includes participants of SafeTREC's Community Pedestrian and Bicycle Safety Training Program, academics, researchers, alumni, students, traffic safety professional, advocates, community based organizations.

The survey was first distributed on March 16, 2023 to the SafeTREC mailing lists and then to bicycle advocacy and cycling clubs on March 28, 2023. The survey was closed on May 5, 2023.

Some of the bicycle advocacy and cycling clubs that were contacted include:

- Bike East Bay
- San Francisco Bicycle Coalition
- Active San Gabriel Valley
- Bicycling Monterey
- Sacramento Area Bicycle Advocates
- Alto Velo Racing
- Bike Lodi
- West Hollywood Bicycle Coalition
- Marin Cyclists
- Bike Davis
- California Bicycle Coalition
- Velo Girl

While the organizations that were contacted are all based in California, we do not know whether all respondents are currently California residents. So long as an individual was signed up to receive emails from any of the organizations we contacted, that person could have taken the survey, regardless of where they were living. For future projects, we recommended adding a third screening question to ensure that all respondents are California residents.

The flyers used for the outreach process can be found in the Appendix.

Compensation

To encourage individuals to take the survey, a couple of monetary incentives were provided. First, a drawing was created to give out six gift cards: one for $150, two for $75, and three for $50. Anyone who completed the survey had the opportunity to enter into the drawing. Second, to encourage participation of individuals from minority communities or traditionally underrepresented communities, we provided a $10 gift card to anyone who completed the survey that was a member of these communities. Only individuals who had received the link to the survey via an email sent by our CBO partners had the opportunity to receive the $10 gift card. No additional screening was conducted to make sure that participants were indeed from these communities. Participants from these communities were also able to enter into the drawing for the six gift cards.

Data Cleaning Procedure

After conducting data cleaning, we received a total of 909 valid responses, which were carefully filtered from the initial pool of 1,654. Fifteen of the 909 were from members of underrepresented communities. The following are the criteria we used to remove responses:

1. Reponses with a completion time that was less than 7 minutes
2. Responses from an IP address that was repeated more than twice
3. Incomplete responses to all demographic questions or questions about biking habits
4. Incomplete responses to all 15 choice questions
5. Responses that chose the same alternative for all 15 of the choice questions
6. Responses that had the same answer for all Likert-scale questions

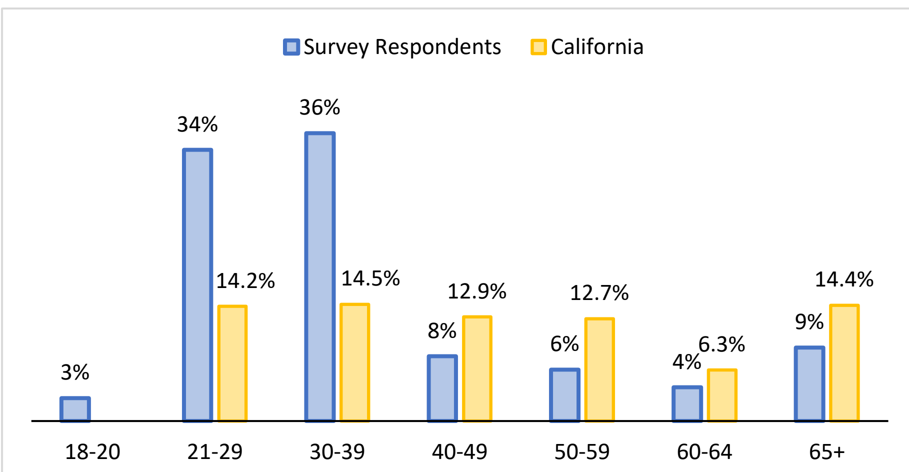
Survey Results

Table 10 and Figure 6 summarize demographic data of the survey respondents. To assess the representativeness of the survey sample, we have included California demographic data for comparison. Overall, the majority of respondents identified as White (83%), not Hispanic (78%), male (61%), and between ages 21 and 40 (70%). Approximately 40% of responses were from female identifying individuals. Comparing the survey data to California's population, certain disparities are evident, particularly concerning gender, race, and age. Our survey appears to be skewed when compared to California's overall population.

Table 10. Demographic Characteristics of Survey Respondents

	Survey Respondents		California	
	Count	%	Count	%
Sample Size	909	100	39,455,353	100
Gender				
Male	553	60.8	19,714,044	50
Female	349	38.4	19,741,309	50
Non-binary	7	0.8	-	-
Race				
White	748	82.3	20,553,732	52.1
American Indian or Alaska Native	60	6.6	360,607	0.9
Asian	28	3.1	5,887,396	15.0
Black or African American	22	2.4	2,233,258	5.7
Native Hawaiian or other Pacific Islander	21	2.3	148,278	0.4
Other	17	1.9	6,036,865	15.3
Two or More Races	13	1.4	4,235,217	10.7
Ethnicity				
Hispanic	200	22	15,593,787	39.5

Notes: California estimates were obtained from the 2021 ASC 5-year estimates, Tables B03002 and S0101. The ASC does not report on number of non-binary individuals.



Notes: California estimates were obtained from the 2021 ASC 5-year estimates, Table S0101. Age bin 18-20 is not include for California as the Census does not report that age category.

Figure 6. Age Distribution of Survey Respondents

Regarding respondents' bicycling habits, the majority are frequent bikers that travel a range of distances every week, and care about their safety, as indicated by the high helmet use (Table 11). The vast majority bike every day or a few times a week (90%), and 40% travel a weekly distance of 5-19 miles. A quarter of respondents travel more than 40 miles, suggesting that they may participate in long cycling tours for leisure. Looking at bike car and bike ownership, all respondents either own a car or have a car available in their household. This finding may suggest that respondents bike because they voluntarily choose to do so and not out of necessity.

Table 11. Survey Respondents' Biking Habits

	Count	%
Sample Size	909	100
Bike ownership		
Yes	903	99.4
No	6	0.6
Car ownership		
I own a car	757	83.3
A car is available for me to use	152	16.7
None of the above	0	0
Bike frequency		
Everyday	205	67.9
A few times a week	618	22.5
A few times a month	68	7.48
Rarely	18	1.9
Distance travelled in a week		
< 5 mi	110	12.1
5-19 mi	357	39.3
20-40 mi	211	23.2
> 40 mi	357	25.4
Helmet Use		
Always	738	81.1
Usually	110	12.1
Sometimes	45	4.9
Seldom	9	0.9
Never	7	0.8
Have a medical condition that prevents them from riding more	219	24

Respondents bike for a variety of reasons, most notably for recreation or fitness. Around 70% of respondents selected recreation as one of the purposes of their bike trips. The rest of the times they travel on a bike for commuting or other casual activities like shopping or traveling to meet people (Figure 7). Only a select few (< 10%) bike to commute only, while a significant amount (20%) exclusively bike for recreation.

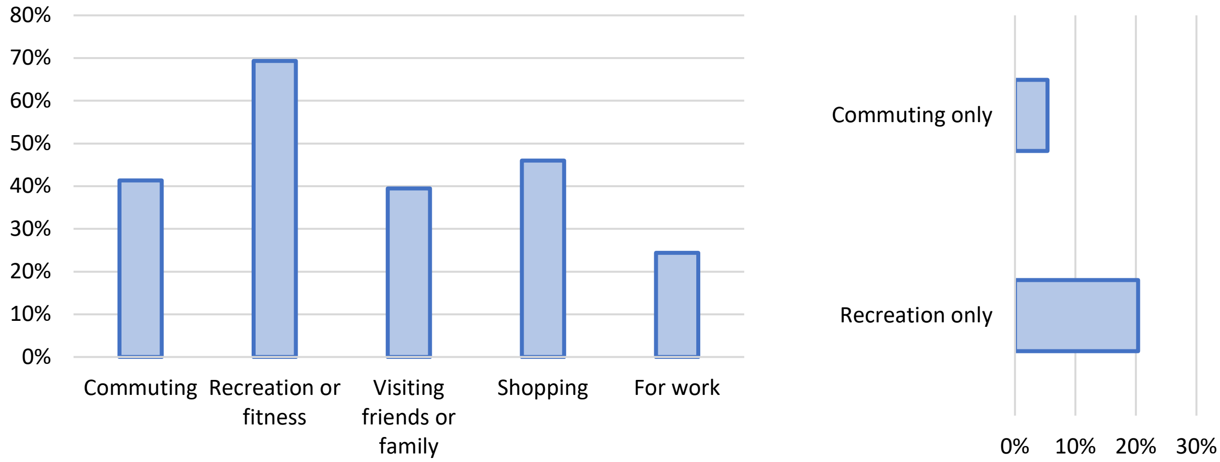


Figure 7. Survey Respondents' Bike Trip Purposes

Survey respondents stated that bicycle infrastructure and roads with low traffic volumes are important factors for selecting their bicycle routes (Figure 8). In particular, more than 50% responded that separation from cars, roads with low speed traffic, marked bike lanes, and roads with low traffic are either extremely important or very important when defining their routes. Only 1% stated that none of these are important. This highlight the critical role that roadway conditions and the availability of bike facilities have in promoting a sense of comfort for bicyclists.

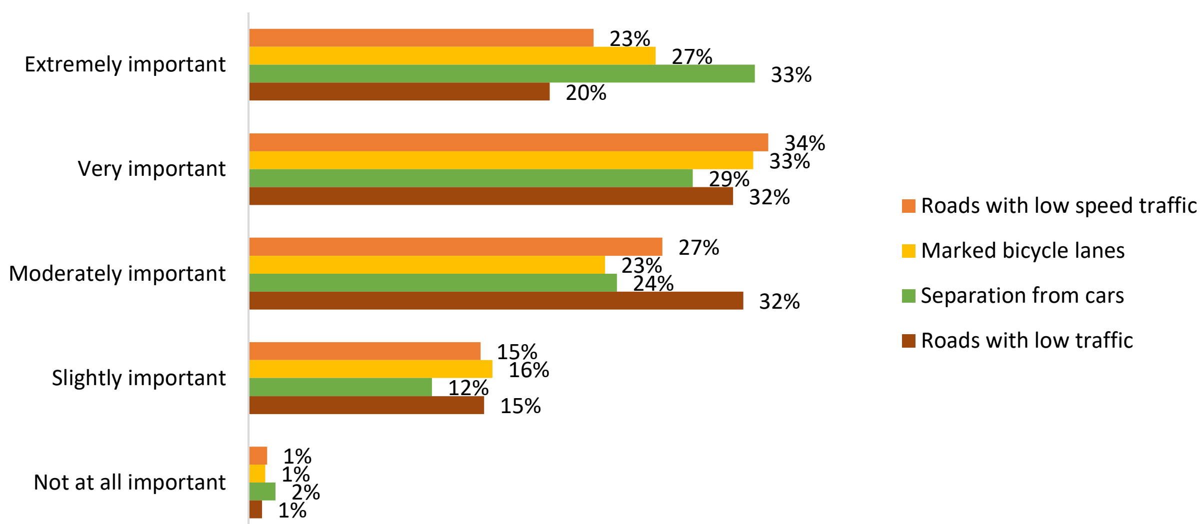


Figure 8. Survey Results: Importance of Route Elements

The sample comprises a group of individuals who hold a positive inclination towards biking, yet exhibit a range of opinions regarding their perceptions of safety and comfort while engaging in this activity (Figure 9). While the majority of respondents expressed feeling safe while biking, it is noteworthy that a significant portion (20%), did not. Furthermore, 35% agreed that "bicycling is a high risk activity" and an even higher percentage (62%) stated that they would "bike more if it felt safer and more comfortable" to do so. These findings underscore the importance of addressing safety concerns and enhancing biking comfort to promote and encourage increased bicycling participation among individuals who already have positive attitudes towards biking.

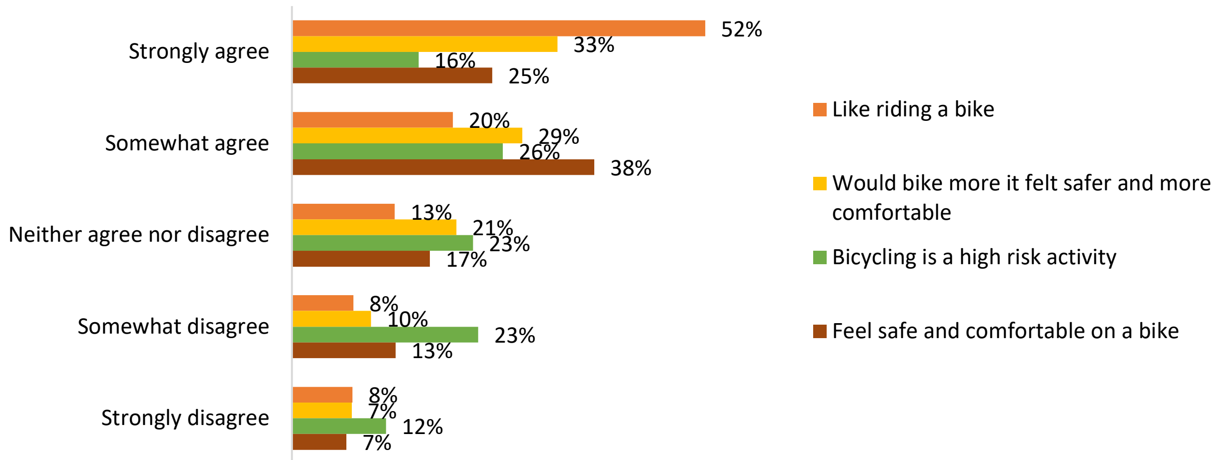


Figure 9. Survey Results: Biking Level of Comfort and Safety

Overall, our survey collected some diversity of responses from individuals with varying biking habits and perceptions about biking. The vast majority of respondents are frequent bikers between the ages of 21-40 that like to bike and do so for a variety of purposes, but in particular for recreation. This aligns with our expectations, as the survey was primarily distributed to bicycle clubs and advocacy groups whose members possess a high level of biking skill and interest. Yet, despite the prevailing trend, we did receive input from individuals of all age groups, genders, and different biking habits and preferences. Notably, respondents expressed a range of opinions concerning bike comfort and safety, pointing to some heterogeneity. These varying perspectives present an opportunity to employ a Latent Class Choice Model for recognition and analysis.

Latent Class Choice Models

Two Latent Class Choice Models (LCCM) were estimated for the development of the BLOS metric. A LCCM is a type of discrete choice model that segments the population into discrete groups or classes to capture unobserved heterogeneity in the choice process. Classes are defined based on the assumption that individuals in each class have similar choice preferences. Hence, the population can be probabilistically divided into segments with different decision criteria. Traditionally, latent classes are defined by the socio-demographic characteristics of individuals, but for the development of the BLOS, additional variables that capture individuals' biking infrastructure preferences and travel habits were incorporated. The estimated classes represent the different types of bicyclists in California, and each class has its own utility equation within the LCCM. These utility equations and the probabilities they generate can form the basis of new BLOS measures.

Background

A Latent Class Choice Model (LCCM) consists of two sub-models: a class membership model and a class-specific choice model. The class membership model calculates the probability that a bicyclist belongs in class k, while the choice model calculates the probability that a bicyclist chooses alternative i, given that the biker belongs to a certain class. Because the classes are latent and we do not know in advance the class to which each individual belongs to, the parameters for the class membership and choice models are estimated simultaneously.

The class membership model is defined as a multinomial logit, where the utility of an individual *n* belonging in class *k* can be defined as:

$$U_{nk} = ASC_k + Z_n\gamma_k + \varepsilon_{nk}$$

where ASC_k is the alternative specific constant for each class k, Q_n is a vector containing the characteristics of individual n, γ_k is a vector of unknown parameters, and ε_{nk} is an error term that is assumed to be independently and identically distributed Extreme Value across individuals and classes. Thus, the probability that an individual n belongs to class k is given by:

$$P(k|Z_n) = \frac{e^{Z_n\gamma_k}}{\sum_{k'=1}^{K} e^{Z_n\gamma_{k'}}}$$

The class-specific choice model calculates the probability that individual n choses alternative i, given that they belong in class k. The utility is formulated as follows:

$$U_{ni|k} = V_{ni|k} + \varepsilon_{nk} = ASC_i + X_{ni}\beta_k + \varepsilon_{ni|k}$$

where $V_{ni|k}$ is the observed part of the utility, ASC_i is the alternative specific constant for alternative i, X_{ni} is a vector of observed attributes of alternative i, β_k is a vector of unknown parameters, and $\varepsilon_{ni|k}$ is an error term that is assumed to be independent and identically distributed across alternatives. Thus, the probability that individual n chooses alternative i, given that they belong in class k is defined as:

$$P(i = 1|X_n, k) = \frac{e^{V_{ni|k}}}{\sum_{j'=1}^{J} e^{V_{nj'|k}}}$$

Finally, the overall probability that a bicyclist chooses alternative i is formulated as:

$$P(i = 1|X_n, Z_n) = \sum_k P(i = 1|X_n, k)P(k|k_n)$$

Model Specification

The variables that were ultimately included in the models came as a result of a long process of testing combinations of variables and eliminating those that do not significantly add to the models. For the class model, several new variables that represent larger abstract concepts were created in order to simplify interpretation of the models. For instance, the variable "want bike infrastructure", represents individuals who stated that separation from traffic and marked bike lanes were either extremely important or very important to them when selecting their bike route. Similarly, "bike frequently" includes individuals who bike either every day or a few times a week. The final list of variables included in the Q_n vector are listed in Table 12.

Table 12. Class Model Variables

Variable name	Type	Question	Response
Female	Dummy variable	"What is your gender?"	"Female": 1 All other responses: 0
Age 40+	Dummy variable	"What is your age?"	"40-49": 1 "50-59": 1 "60-64": 1 "65+": 1 All other responses: 0
Want bike infrastructure	Dummy variable	"Rate the following factors based on how important they are to when you select a bicycle route: separation from cars, separation from cars"	"Extremely important": 1 "Very important": 1 "Moderately important": 0 "Slightly important": 0 "Not at all important": 0
Bike frequently	Dummy variable	"How often do you ride a bicycle?"	"Everyday": 1 "A few times a week": 1 "A few times a month": 1 " Rarely": 0 "I never ride a bike": 0
Like biking	Dummy variable	"Rate the following statements based on how much you agree or disagree with them: I like riding a bike"	"Strongly agree": 1 "Somewhat agree": 1 "Neither agree nor disagree": 0 "Somewhat disagree": 0 "Strongly disagree": 0

Variable name	Type	Question	Response
Trip purpose: recreation only	Dummy variable	"What are the typical purposes of your bicycle trips? Select all that apply"	Recreation only: 1 All other response: 0

For the class-specific choice model, a multinomial logit model with three alternatives was defined for the estimation of the LCCMs. The first two alternatives embody the two videos that respondents were asked to choose between and their utility equations are identical. The third alternative is the opt-out option or the "I would choose not to ride a bike" option which respondents could select when they answered the question: "If these were the only two options available, would you choose to ride a bike?". The opt-out alternative, which represents a roadway segment with no bike infrastructure and no traffic, serves as the base from which worsening traffic conditions and the availability of bike facilities are evaluated.

$$V_{Video1} = ASC + X_{nVideo1}\beta_k$$

$$V_{Video2} = ASC + X_{nVideo2}\beta_k$$

$$V_{Opt-out} = 0$$

Finally, for the dependent variable, respondents' choices, which were originally coded as a 5-scale rating level, were simplified to two choices. If respondents chose "Probably A" or "Definitely A" we simply coded that as choosing A. Similarly, "Probably B" or "Definitely B" were grouped together. "Indifferent" responses were dropped.

Model Results & Discussion

We estimated two models. Model 1, with three classes, is a constrained version of Model 2, with four classes, and both include the same variables in the class membership and class-specific choice models. The estimation results for the models are presented in Table 13 and 14. We chose these models based on a combination of statistics (t-stat, AIC, BIC) and reasonable interpretation.

It should be noted that estimation of LCCMs can prove challenging due to a number of reasons. LCCMs involve high dimensionality, requiring the estimation of parameters for both the class membership model and class-specific choice models. Given that the likelihood function has multiple local maximum, identifiability issues can arise, where multiple parameter configurations yield similar likelihood values, leading to difficulties in uniquely determining model parameters. Moreover, the model is highly sensitive to initial parameter values, leading to different parameter estimates for different starting values. Thus, the modeling process involves running multiples models, and model selection is based on statistical significance, interpretation, and its alignment with an underlying theoretical framework.

Our best models are models that we considered were the most interpretable and significant in the class-specific choice models. That is, our interpretation of the classes yielded is based on the differences in coefficients representing bike infrastructure, roadway conditions, and traffic conditions, and not necessarily from interpretation of the class membership model.

That said, the two models we present here are very closely related. In both, the class representing *Road Cycling Enthusiasts* and those who are *Indifferent to Infrastructure* are very similar. The share of individuals in each class is relatively the same in Model 1 and 2, and the signs of the coefficients are also the same. *Road Cycling Enthusiasts* are 7% and 10% in Model 1 and 2, respectively. *Indifferent to Infrastructure* represent 39% in both models.

The main difference between the two models lies in the class representing *Occasional Recreational Bicyclists*, where it can be observed that the class splits into two when estimating for a fourth class. The share of *Occasional Recreational Bicyclists* goes from 53% in Model 1, to splitting into 27% and 25% in Model 2. We note significant differences in the coefficients for bike infrastructure variables such that we can sub-divide *Occasional Recreational Bicyclists* into those who show a high sensitivity to bike facilities (*High Sensitivity to Infrastructure)* and those who show a moderate sensitivity to bike facilities (*Moderate Sensitivity to Infrastructure)*, based on the magnitude of the bike facility variables.

Interpretation of the class membership model to understand who falls under *High Sensitivity to Bike Infrastructure* and *Moderate Sensitivity to Bike Infrastructure* is not straightforward, however. There are multiple variables in the class membership model that interact in different ways, making it difficult to discern the exact relationship between individual characteristics (bike frequency, age, gender, etc.) and the class membership. Thus, we included both models to demonstrate some of the challenges with interpreting an LCCM. Model 1 defines *Occasional Recreational Bicyclists* as people who are 40+ old, bike a few times a month or less and do so for recreation only. Yet, when split into *High and Moderate Sensitivity to Bike Infrastructure* it is not clear what the demographic differences are between the two classes. The magnitude of the coefficients for the variables representing individual characteristics are very similar and their signs identical. We run into similar challenges when trying to characterize who falls under Class 4. It may be possible that there are other variables that can help clarify the demographic differences between classes that our survey did not include.

Given the challenges with interpretability of the class model, we limit our interpretation of classes to that of the class-specific choice model. We chose to interpret Model 2 in detail due to the high number of significant variables in the class-specific choice models. The following is our interpretation of the bicyclist typology:

Road Cycling Enthusiasts (Class 1 - 7%): Members of this class are individuals that are 40+ years old that bike a few times a month or less, and typically bike for recreational purposes only. The large positive constant in the choice model indicates that they have a strong inclination towards biking and would likely choose to bike on any street, regardless of the type of infrastructure available. Road cycling enthusiasts respond positively to bike lanes, dislike buffers of any kind (barriers, median, parking lanes, simple buffer strips), and prefer to bike on multi-lanes streets and avoid streets with high traffic volumes.

Occasional Recreational Bicyclists - Moderate Sensitivity to Bike Infrastructure (Class 2- 25%): Members of this class are also 40+ years old, do not bike frequently, and consider bike infrastructure to be more important to them than *Road Cycling Enthusiasts.* Members of this class inherently prefer not to ride a bike, as indicated by the negative constant in the choice model. They respond positively to bike facilities like bike lanes, buffers, and barriers for protection, and prefer to ride roads with light traffic, a small percentage of heavy-duty vehicles, and with good pavement conditions. They respond particularly well to medians.

Occasional Recreational Bicyclists - High Sensitivity to Bike Infrastructure (Class 3 -27%): Members of this class are identical to Class 2 based on individual characteristics. They differ from Class 2 in that they show a higher sensitivity to bike infrastructure and poor traffic conditions than Class 2, as indicated by the larger magnitude of the coefficients for bike lanes, buffers, all barrier types, good quality pavement, and one lane streets. They respond particularly positively to barriers (e.g. bollards) and medians as protective measures from cars.

Indifferent to Bike Infrastructure (Class 4 - 39%): The class membership model indicates that members of this class are individuals for whom bike infrastructure is not very important when choosing their bike route. Such perspective is reflected in the relatively small coefficients for bike infrastructure, traffic, and roadway surface, which indicate that these individuals have a weaker, almost neutral, response to most bike infrastructure, especially compared to the other classes. Members of this class are frequent bikers who bike for a variety of reasons beyond recreation.

In summary, our models demonstrate that there is heterogeneity between the individuals that took our survey concerning their preferences for various types of bike facilities, roadway and traffic conditions. This diversity allows us to categorize individuals along a scale of preferences, ranging from those who are relatively indifferent to those with a strong sensitivity to bike infrastructure. Moreover, we have identified a group with very particular preferences. These individuals clearly favor riding on low-traffic roads, multi-lanes roads with bike lanes but with no barriers separating them from cars. This preference profile closely aligns with that of road cyclists.

Table 13. Model 1: Three-Class LCCM

	CLASS 1 Road Cycling Enthusiasts 7%		CLASS 2 Occasional Recreational Bikers 53%		CLASS 3 Indifferent to Infrastructure 39%	
Class Membership Model						
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	-4.11***	-2.15	-0.49	-0.90	Base	
Female (1=y, 0= n)	-0.84***	-2.61	-0.69***	-2.98		
Age 40+ (1=y, 0=n)	9.55***	18.4	9.99***	21.00		
Bike frequently (1=y, 0=n)	1.70	0.89	-0.69	-1.63		
Trip purpose: recreation only (1=y, 0=n)	2.06***	4.92	1.73***	5.43		
Want bike infrastructure (1=y, 0=n)	0.53	1.30	1.61***	6.61		
Class-Specific Choice Model						
Constant	9.22***	2.42	-0.31***	-1.46	0.16	1.06
Traffic volume/1,000	-1.47***	-3.06	-0.05**	-1.72	-0.02	-0.97
One lane street	-1.19**	-1.69	0.14***	2.09	0.04	0.67
% Heavy-duty Vehicles	0.34	0.90	-0.07***	-3.59	0.01	0.24
Bike lane width	1.74***	3.22	0.23***	11.60	0.03	1.53
Buffer width	-1.03***	-2.15	0.11***	5.91	-0.01	-1.03
Buffer type: barrier	-2.53	-0.87	1.04***	6.94	0.07	0.64
Buffer type: median	-0.84	-0.36	1.42***	10.10	0.03	0.23
Buffer type: parking spot	-1.68	-0.98	0.35***	2.73	0.22**	1.87
Pavement quality: good quality	-0.84	-0.63	0.68***	8.43	-0.04	-0.66
Null LL	-13,628.29					
LL	-11,119.75					
BIC	22,635.39					
AIC	22,323.5					
Adjusted Rho-squared	0.18					
Number of respondents = 909						
Number of observations = 2,405						

Notes: *** and ** indicate significance at the 95% and 90% confidence levels

Table 14. Model 2: Four-Class LCCM

	CLASS 1 Road Cycling Enthusiasts 10%		CLASS 2 Moderate Sensitivity to Bike Infrastructure 25%		CLASS 3 High Sensitivity to Bike Infrastructure 27%		CLASS 4 Indifferent to Infrastructure 39%	
Class Membership Model								
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-2.35	-1.52	1.24	1.33	-1.44	-0.83	Base	
Female (1=y, 0= n)	-1.74***	-2.07	-0.29	-0.57	-1.93***	-2.10		
Age 40+ (1=y, 0=n)	10.50***	8.96	8.49***	8.90	11.20***	8.51		
Bike frequently (1=y, 0=n)	-0.42	-0.26	-3.94***	-3.50	-1.01	-0.60		
Trip purpose: recreation only (1=y, 0=n)	3.34***	3.87	2.58***	2.66	3.28***	3.83		
Want bike infrastructure (1=y, 0=n)	1.61***	2.62	2.95***	4.19	2.28***	3.71		
Class-Specific Choice Model								
Constant	8.03***	5.29	-0.82***	-2.42	-0.64	-1.12	0.18	1.27
Traffic volume/1,000	-0.60***	-3.83	-0.12***	-3.41	-0.04	0.57	-0.02	-0.72
One lane street	-1.94***	-2.85	0.19	1.42	0.44***	2.43	0.07	1.17
% Heavy-duty Vehicles	-0.33***	-4.03	-0.03	-1.46	-0.02	-0.74	0.01	1.20
Bike lane width	0.69***	5.04	0.23***	7.57	0.30***	6.27	0.04**	1.94
Buffer width	0.14	1.13	0.03	1.11	0.09***	2.82	-0.01	-1.05
Buffer type: barrier	-7.46***	-4.40	0.90***	4.47	2.58***	5.60	0.15**	1.69
Buffer type: median	-4.04***	-3.25	1.44***	6.45	2.63***	5.71	0.04	0.39
Buffer type: parking spot	-4.67***	-2.86	0.60***	2.47	0.98***	2.67	0.21**	1.88
Pavement quality: good quality	-1.54***	-2.48	0.61***	4.29	0.88***	4.82	-0.04	-0.63
Null LL	-13,628.29							
LL	-11,011.21							
BIC	22,569.12							
AIC	22,138.42							
Adjusted Rho-squared	0.19							
Number of respondents = 909								
Number of observations = 12,405								

Notes: *** and ** indicate significance at the 95% and 90% confidence level

BLOS METRIC DEVELOPMENT

Having identified distinct groups of people with distinct biking preferences, new BLOS metrics can be constructed using the utility equations estimated for each group. Here we present one example of the potential use of the equations but future work should explore more opportunities in depth.

The LCCM results can be used to calculate the probabilities that a class of individuals would ride a given roadway segment. To estimate the probabilities, various alternatives must be compared against each other. For instance, various road configurations can be compared to a base case with a street with no bike facilities. In that way, changes in the probabilities can be tracked with each added bike infrastructure element.

Tables 15-18 show the probability that individuals choose to ride on a road with the specified features versus a road with no bike infrastructure (V=0). For both options, the traffic volume and percentage of heavy-duty vehicles on the road is zero, but this could be adjusted as necessary. We used the class-specific choice parameters estimated for Model 2 (Table 14) to estimate the probabilities. We chose to highlight in green probabilities that are higher than 0.75, but his threshold can be adjusted to the any desired value.

Table 15. Road Cycling Enthusiasts BLOS

		One lane street	One lane street	One lane street	One lane street	One lane street	Multi-lane street	Multi-lane street	Multi-lane street	Multi-lane street	Multi-lane street
		Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width
Barrier	Buffer	0'	2'	3'	5'	7'	0'	2'	3'	5'	7'
No barrier	3'	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
No barrier	7'	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
No barrier	11'	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Barrier	3'	0.280	0.606	0.754	0.924	0.980	0.729	0.914	0.955	0.988	0.997
Barrier	7'	0.405	0.730	0.843	0.955	0.988	0.825	0.949	0.974	0.993	0.998
Barrier	11'	0.545	0.826	0.904	0.974	0.993	0.893	0.970	0.985	0.996	0.999
Median	3'	0.922	0.979	0.989	0.997	0.999	0.988	0.997	0.998	1.000	1.000
Median	7'	0.954	0.988	0.994	0.998	1.000	0.993	0.998	0.999	1.000	1.000
Median	11'	0.973	0.993	0.997	0.999	1.000	0.996	0.999	1.000	1.000	1.000
Parking lane	3'	0.864	0.962	0.980	0.995	0.999	0.978	0.994	0.997	0.999	1.000
Parking lane	7'	0.918	0.978	0.989	0.997	0.999	0.987	0.997	0.998	1.000	1.000
Parking lane	11'	0.951	0.987	0.994	0.998	1.000	0.993	0.998	0.999	1.000	1.000

Table 16. Occasional Recreational Riders – High Sensitivity to Bike Infrastructure

		One lane street	One lane street	One lane street	One lane street	One lane street	Multi-lane street	Multi-lane street	Multi-lane street	Multi-lane street	Multi-lane street
		Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width	Bike lane width
Barrier	Buffer	0'	2'	3'	5'	7'	0'	2'	3'	5'	7'
No barrier	3'	0.520	0.666	0.730	0.833	0.902	0.411	0.563	0.636	0.763	0.855
No barrier	7'	0.611	0.743	0.797	0.879	0.930	0.503	0.651	0.717	0.823	0.896
No barrier	11'	0.695	0.808	0.851	0.913	0.951	0.595	0.730	0.786	0.871	0.926
Barrier	3'	0.935	0.963	0.973	0.985	0.992	0.902	0.944	0.958	0.977	0.987
Barrier	7'	0.954	0.974	0.981	0.990	0.994	0.930	0.961	0.971	0.984	0.991
Barrier	11'	0.968	0.982	0.987	0.993	0.996	0.951	0.973	0.980	0.989	0.994
Median	3'	0.938	0.965	0.974	0.986	0.992	0.906	0.947	0.960	0.978	0.988
Median	7'	0.956	0.976	0.982	0.990	0.995	0.934	0.963	0.972	0.985	0.992
Median	11'	0.969	0.983	0.987	0.993	0.996	0.953	0.974	0.981	0.989	0.994
Parking lane	3'	0.742	0.841	0.878	0.930	0.961	0.650	0.774	0.823	0.895	0.940
Parking lane	7'	0.807	0.885	0.913	0.951	0.973	0.729	0.832	0.871	0.925	0.958
Parking lane	11'	0.858	0.918	0.938	0.965	0.981	0.796	0.878	0.907	0.947	0.971

Table 18. Occasional Recreational Riders – Moderate Sensitivity to Bike Infrastructure

		One lane street Bike lane width	One lane street Bike lane width	One lane street Bike lane width	One lane street Bike lane width	One lane street Bike lane width	Multi-lane street Bike lane width	Multi-lane street Bike lane width	Multi-lane street Bike lane width	Multi-lane street Bike lane width	Multi-lane street Bike lane width
Barrier	Buffer	0'	2'	3'	5'	7'	0'	2'	3'	5'	7'
No barrier	3'	0.368	0.482	0.540	0.652	0.749	0.324	0.433	0.490	0.605	0.710
No barrier	7'	0.393	0.508	0.566	0.675	0.768	0.347	0.459	0.517	0.630	0.731
No barrier	11'	0.418	0.534	0.591	0.698	0.786	0.371	0.485	0.543	0.654	0.751
Barrier	3'	0.590	0.697	0.743	0.822	0.880	0.542	0.653	0.704	0.791	0.858
Barrier	7'	0.615	0.718	0.763	0.837	0.891	0.567	0.677	0.725	0.808	0.870
Barrier	11'	0.640	0.739	0.781	0.851	0.901	0.593	0.699	0.746	0.824	0.882
Median	3'	0.711	0.797	0.832	0.887	0.926	0.668	0.763	0.802	0.866	0.912
Median	7'	0.732	0.813	0.846	0.898	0.933	0.691	0.781	0.818	0.878	0.920
Median	11'	0.752	0.829	0.859	0.907	0.939	0.713	0.799	0.833	0.889	0.927
Parking lane	3'	0.516	0.629	0.682	0.774	0.845	0.466	0.582	0.638	0.737	0.817
Parking lane	7'	0.542	0.654	0.704	0.792	0.858	0.493	0.607	0.661	0.757	0.832
Parking lane	11'	0.568	0.677	0.726	0.808	0.871	0.519	0.632	0.685	0.776	0.847

Table 17. Indifferent to Bike Infrastructure

		One lane street Bike lane width	One lane street Bike lane width	One lane street Bike lane width	One lane street Bike lane width	One lane street Bike lane width	Multi-lane street Bike lane width	Multi-lane street Bike lane width	Multi-lane street Bike lane width	Multi-lane street Bike lane width	Multi-lane street Bike lane width
Barrier	Buffer	0'	2'	3'	5'	7'	0'	2'	3'	5'	7'
No barrier	3'	0.555	0.573	0.582	0.599	0.616	0.537	0.555	0.564	0.582	0.599
No barrier	7'	0.545	0.563	0.572	0.589	0.606	0.527	0.545	0.554	0.572	0.589
No barrier	11'	0.535	0.552	0.561	0.579	0.597	0.517	0.535	0.544	0.562	0.579
Barrier	3'	0.591	0.608	0.617	0.633	0.650	0.573	0.591	0.600	0.617	0.634
Barrier	7'	0.581	0.598	0.607	0.624	0.641	0.563	0.581	0.590	0.607	0.624
Barrier	11'	0.571	0.588	0.597	0.614	0.631	0.553	0.571	0.580	0.597	0.614
Median	3'	0.564	0.582	0.591	0.608	0.625	0.547	0.565	0.573	0.591	0.608
Median	7'	0.554	0.572	0.581	0.598	0.615	0.536	0.554	0.563	0.581	0.598
Median	11'	0.544	0.562	0.571	0.588	0.606	0.526	0.544	0.553	0.571	0.588
Parking lane	3'	0.606	0.623	0.631	0.648	0.664	0.588	0.606	0.614	0.631	0.648
Parking lane	7'	0.596	0.613	0.621	0.638	0.655	0.578	0.596	0.605	0.622	0.638
Parking lane	11'	0.586	0.603	0.612	0.629	0.645	0.568	0.586	0.595	0.612	0.629

The tables above illustrate how the probability of riding on a particular road segment changes as the configuration of the bike facilities change. In general, it can be observed that the probability of riding on a road segment with any bike facility versus one that has no bike facilities increases as new features are added and as the dimensions of those features increase. Values increase as they approach the bottom left corner of the tables. This holds true for all classes except for those *Indifferent to Bike Infrastructure,* who react negatively towards buffers per their utility equation.

The tables also shed light into the minimum configuration needed to encourage users to bike. *Road Cycling Enthusiasts* require the least infrastructure to bike as they already have a high inclination towards biking, no matter the road conditions. *Occasional Recreational Bicyclists* with a high sensitivity to bike facilities respond immediately positively to roads that have any type of infrastructure. A 3' bike lane with no buffer or a street with any barrier that separates them from traffic is enough to encourage them to bike. *Occasional Recreational Bicyclists* with a moderate sensitivity to bike facilities require wider facilities and more separation from cars to increase their chances of riding on that road. The more protection they can get from vehicles, the higher the chances of them choosing to ride a bike.

It should be noted that the interpretation of these tables will change if a different threshold is selected. Had we chosen a threshold of 0.5, all facilities would have led to individuals choosing to bike, given that all probabilities are greater than 0.5. At a larger conceptual level what this reveals is simply that *any* bike infrastructure is enough to increase the chances of people biking on that road, a statement that may seem trivial. There is more value, then, in looking at the values of the probabilities, as they better illustrate the quantitative effects bike infrastructure can have on whether individuals feel comfortable riding on a street.

Lastly, development of BLOS metrics with the estimated utility equations warrants some level of caution. The coefficients of the utility equations indicate the weight or importance a given feature has on an individual's choice to ride a bike. The collective interpretation of the models' coefficients' signs and values helped name the types of people that fall within each class. At a conceptual level, the utility parameters make sense, but when applied as is, they can lead to counter-intuitive results. For instance, individuals who are *Indifferent to Bike Infrastructure* have a weak response to bike facilities. In particular, they have a negative response to bike buffers. Table 18 shows how as the buffer width increases, their probability of riding decreases. This result is contradictory as it is reasonable to assume that larger buffers are preferred over narrower ones since they increase separation from vehicles, decreasing the chances of crashes. Similarly, that a *Road Cycling Enthusiast* has a negative reaction towards barriers does not necessarily imply that they would not ride on a street with a protected bike lane. These and other contradictions must be considered carefully when developing BLOS metrics with an LCCM.

Limitations and Future Work

The proposed BLOS methodology does come with certain limitations that require careful consideration for future iterations. Firstly, we acknowledge that the survey's geographical scope might not have been restricted to California residents only due to the lack of an additional screening question. Including such a question would allow to precisely target respondents from California, ensuring the data's relevance to the state's specific biking preferences and concerns. Secondly, to mitigate the risk of receiving insincere or repetitive responses, the number of choice questions could be reduced. By doing so, the overall quality of responses can be enhanced, increasing the likelihood of participants engaging earnestly with the survey and thus improving the estimated model. Thirdly, when estimating the LCCM models, alternative discrete choice models, such as the Nested Logit model, should be considered. Incorporating a Nested Logit with an LCCM may provide a more accurate and statistically representative model of the choice processes faced by respondents. Lastly, to enhance the models' interpretability and provide a more detailed description of each cycling group, additional demographic variables or variables describing biking habits should be considered. Incorporating these variables can provide a better understanding of the characteristics and preferences of individuals within each class identified by the LCCM

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Appendix

Survey

Flyers